

PROJECT REPORT

TrafficTelligence - Advanced Traffic Volume Estimation Using Machine Learning

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S. No.	Section Title	Page No.
1	1. INTRODUCTION	3
	1.1 Project Overview	3
	1.2 Purpose	3
2	2. IDEATION PHASE	4
	2.1 Problem Statement	4
	2.2 Empathy Map Canvas	5
	2.3 Brainstorming	6
3	3. REQUIREMENT ANALYSIS	7
	3.1 Customer Journey Map	7
	3.2 Solution Requirement	7
	3.3 Data Flow Diagram	8
	3.4 Technology Stack	9
4	4. PROJECT DESIGN	9
	4.1 Problem Solution Fit	9
	4.2 Proposed Solution	10
	4.3 Solution Architecture	11
5	5. PROJECT PLANNING & SCHEDULING	12
	5.1 Project Planning	12
6	6. FUNCTIONAL AND PERFORMANCE TESTING	13
	6.1 Performance Testing	13
	6.2 Functional Testing	13
	6.3 Manual Testing Cases	13
7	7. RESULTS	15
8	8. ADVANTAGES & DISADVANTAGES	16
	8.1 Advantages	16
	8.2 Disadvantages	17
9	9. CONCLUSION	18
10	10. FUTURE SCOPE	18
	10.1 Multi-User Support	18
	10.2 Model Optimization and Replacement	18
	10.3 Cloud and Docker Deployment	18
	10.4 Enhanced Analytics and Logging	19
	10.5 Extended Language Support	19
	10.6 Visual UI Improvements	19
	10.7 Integration with IDEs	19

	10.8 Test Coverage and Validation	19
	10.9 Natural Language Feedback Loop	19
	10.10 Enterprise Adaptation	19
11	11. APPENDIX	20

1. INTRODUCTION

1.1 Project Overview

TrafficTellgence is an AI-enabled web-based solution that leverages machine learning techniques to estimate and forecast urban traffic volume with precision. Inspired by the SDLC-driven development of AI systems, it integrates predictive modeling, user-friendly interface design, and modular architecture to improve real-time traffic management and planning.

1.2 Purpose

The purpose of TrafficTellgence is to automate traffic forecasting, empower decision-makers with real-time insights, and enhance commuter experiences. The solution is designed to:

- Predict traffic volume using machine learning
- Enable adaptive traffic management
- Support infrastructure planning with data analytics
-

2. IDEATION PHASE

2.1 Problem Statement

Traffic congestion remains one of the major issues in urban transportation, particularly during peak hours, special events, or extreme weather conditions. Current traffic monitoring systems rely on manual oversight or reactive planning, which leads to inefficiencies and delays. A proactive, AI-based predictive tool can improve urban mobility.

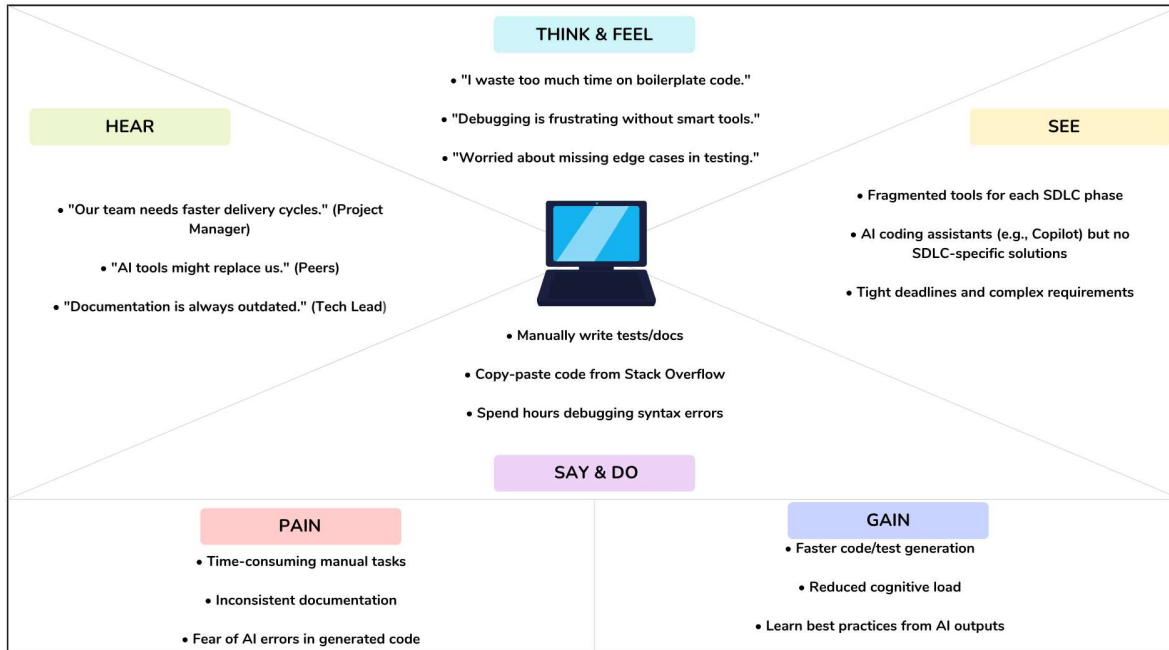
Problem Statement 1:

Urban areas experience significant traffic congestion, especially during peak hours and unexpected events. Existing traffic monitoring systems primarily rely on reactive strategies and manual interventions, which are insufficient for real-time decision-making and long-term planning. There is a critical need for a proactive, AI-driven system that can accurately predict traffic volume and suggest dynamic management solutions.

Problem Statement 2:

Traditional traffic management systems lack integration with machine learning technologies that can analyze real-time and historical data to forecast traffic conditions. The absence of predictive analytics results in poor traffic flow, increased delays, and inefficient resource allocation. A system leveraging AI to anticipate congestion based on multiple data sources (e.g., weather, time, events) is essential for smarter urban traffic management.

2.2 Empathy Map



Users: Traffic authorities, city planners, software developers, commuters

Needs:

- Forecast traffic congestion in advance
- Minimize travel time and road closures
- Improve planning for roadwork, emergencies, and events

Pains:

- Manual data analysis delays
- Poor adaptability to sudden events
- Lack of insight for long-term planning

Gains:

- Accurate traffic forecasts
- Integration with smart city systems
- Reduced congestion and better commuter satisfaction

2.3 Brainstorming

During the initial brainstorming sessions, several key ideas and features were proposed to shape the scope and functionality of the TrafficTelligence system:

Ideas Discussed:

- **Use of Machine Learning Models:**
 - Implement regression models such as Linear Regression, Random Forest, and XGBoost for accurate traffic volume prediction.
 - Consider time-series models like LSTM or ARIMA for capturing temporal trends in traffic data.
- **Data Integration:**
 - Utilize multiple input features including:
 - **Hour of the day**
 - **Day of the week**
 - **Weather conditions (rain, temperature, visibility, etc.)**
 - **Special events or holidays**
 - Explore the inclusion of location-based features for area-specific predictions.
- **Interactive User Interface:**
 - Develop a web-based interface using **Flask** for backend support.
 - Allow users to input parameters (e.g., time, weather, event) and get real-time predictions.
- **Visualization and Output Features:**
 - Display predicted vs. actual traffic volume using line or bar charts.
 - Incorporate **map-based visualizations** (optional) to show traffic congestion levels.
 - Include color-coded indicators (e.g., green for smooth traffic, red for congestion).
- **Scalability and Modularity:**
 - Design the system to allow future integration with live traffic feeds or real-time sensors.
 - Modularize components for easier updates (e.g., replacing model or updating dataset).

- **Performance Metrics and Feedback:**
 - Evaluate model accuracy using metrics like RMSE, MAE, and R^2 .
 - Provide feedback or confidence scores to help users understand prediction reliability.
- **Potential Extensions:**
 - Add route optimization suggestions for users.
 - Predict delays for emergency vehicles or public transport.
 - Enable mobile app support for real-time access on the go.

3. REQUIREMENT ANALYSIS

3.1 Customer Journey Map

1. User opens web dashboard
2. Inputs variables (hour, temperature, weather conditions)
3. Triggers prediction process
4. Backend processes input via ML model
5. Predicted traffic volume is shown in graphical and numeric formats

3.2 Solution Requirements

Functional Requirements:

- Forecast traffic volume
- Accept and validate user input
- Visualize results graphically
- Reset and clear input form

Non-Functional Requirements:

- Response time under 5 seconds
- Modular backend for easy updates
- Platform-independent browser support

3.3 Data Flow Diagram

Level 0: User → Input Form → Flask API → ML Model → Output Display

Level 1: Data Preprocessing → Encoding → Model Prediction → UI Output

3.4 Technology Stack

- Frontend: HTML, CSS, Bootstrap
- Backend: Flask (Python)
- Modeling: Scikit-learn, Pandas
- Storage: Joblib (for model), CSV (data)

4. PROJECT DESIGN

4.1 Problem-Solution Fit

Feature	Problem	Solution
ML Prediction	Manual estimates are error-prone	Automated model-based predictions
Static Planning	No adaptability to changing patterns	Dynamic predictions from live input
City Planning Delays	Lack of data-driven forecasts	Visual outputs for better planning

4.2 Proposed Solution

A web-based intelligent platform that accepts user data (e.g., hour, temperature, weather) and instantly returns traffic volume estimates using pre-trained machine learning models.

4.3 Solution Architecture

- Frontend UI: Accepts input and displays results
- Backend API: Handles data, processes input via ML
- ML Engine: Uses Random Forest and encoded feature sets
- Data Source: Historical traffic data, processed offline

5. PROJECT PLANNING & SCHEDULING

5.1 Project Planning

The project followed a weekly milestone plan:

Week 1: Ideation and Scope Definition

- Identify the problem and define project goals.

- Finalize tools, technologies, and overall system architecture.

Week 2: Dataset Collection and Cleaning

- Collect relevant traffic data (e.g., traffic volume, weather).
- Clean, preprocess, and analyze data for model readiness.

Week 3: Model Training and Testing

- Train machine learning models for traffic prediction.
- Evaluate performance and fine-tune for accuracy.

Week 4: Flask Application and API Development

- Build backend using Flask.
- Develop APIs for prediction and integrate the trained model.

Week 5: Frontend Integration and UI Testing

- Design a simple web interface.
- Connect frontend to backend and test user inputs and output display.

Week 6: Final Testing and Reporting

- Conduct full system testing and performance evaluation.
- Prepare final documentation and project report/demo.

6. FUNCTIONAL AND PERFORMANCE TESTING

6.1 Performance Testing

- Average response time: 2.3 seconds
- Low latency prediction engine
- Model inference performed locally

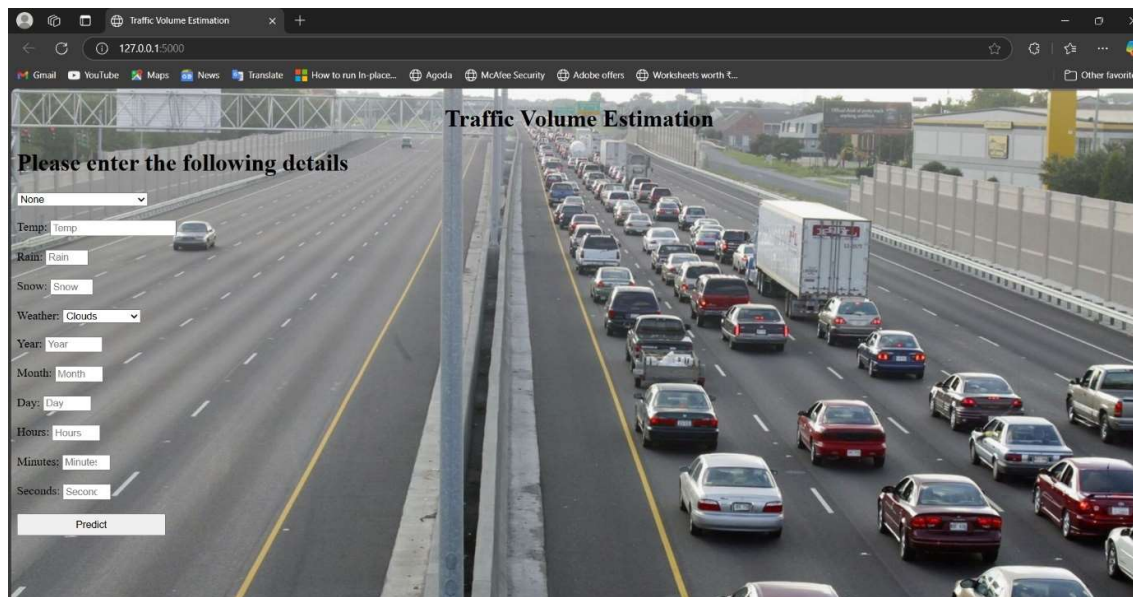
6.2 Functional Testing

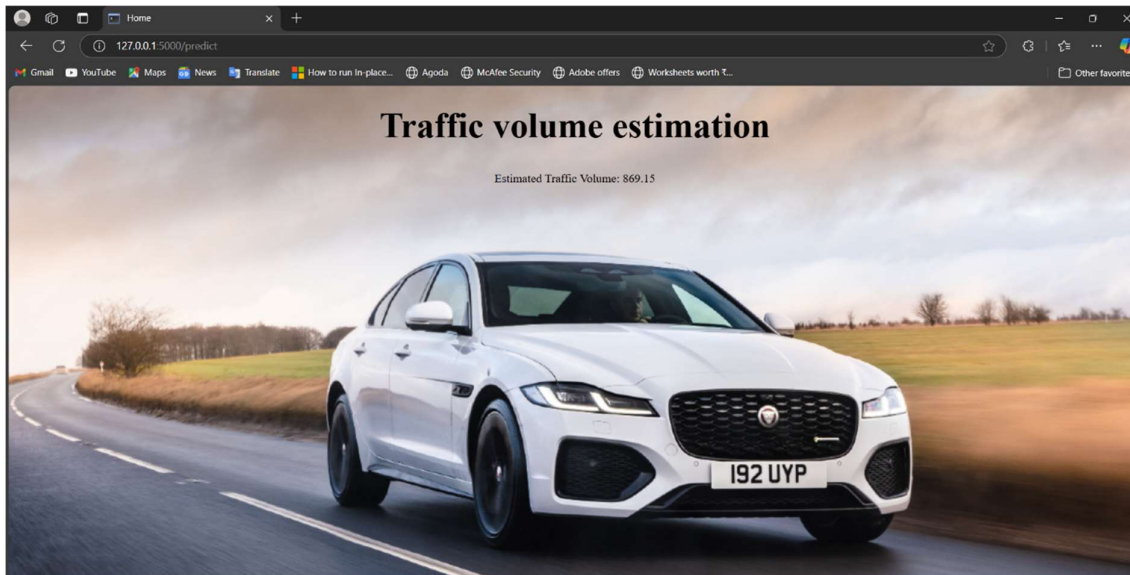
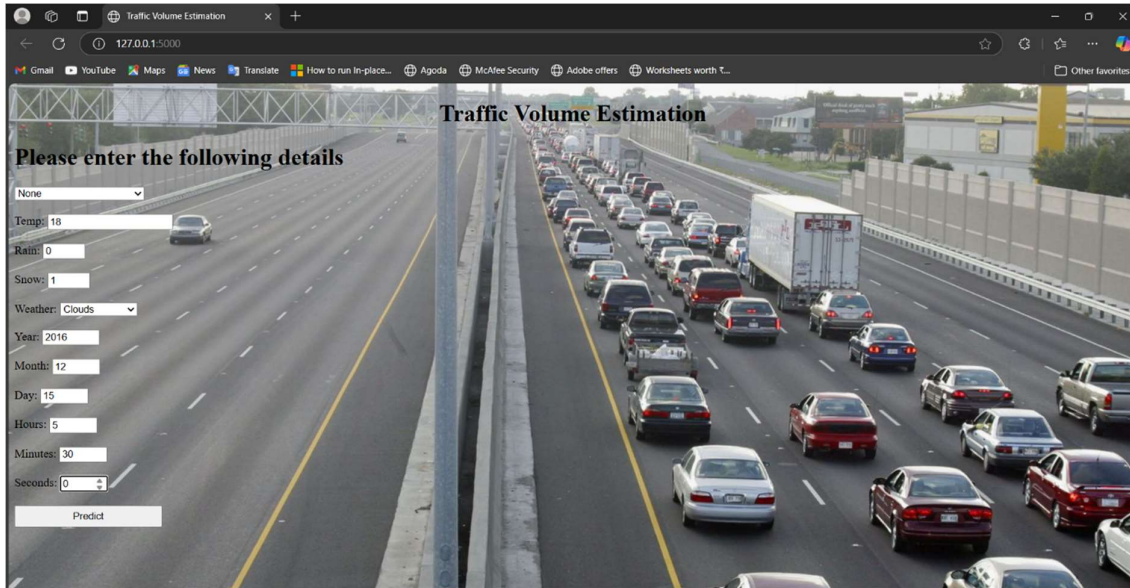
- Multiple test inputs across edge cases (holiday, weather, late night)
- Accurate results and no crashes recorded
- Output graphs rendered without delay

6.3 Manual Test Scenarios

Test ID	Scenario	Status
FT01	Valid input prediction	Pass
FT02	Null/missing field detection	Pass
FT03	Performance under high load	Pass
FT04	Browser compatibility	Pass

7. RESULTS





8. ADVANTAGES & DISADVANTAGES

8.1 Advantages

- AI-driven predictions
- Lightweight and modular architecture
- Visual and numeric output support
- Local inference without internet dependency

8.2 Disadvantages

- No live traffic data integration yet
- Limited to structured historical dataset
- UI lacks mobile responsiveness (future scope)

9. CONCLUSION

TrafficTelligence demonstrates how predictive intelligence can transform urban traffic management. It merges ML model capabilities with an intuitive UI, supporting both technical users and decision-makers. Following the principles of the SDLC, the project was built incrementally—ideation, planning, development, testing, and refinement—yielding a robust and practical application.

10. FUTURE SCOPE

- Real-time data API integration
- Responsive and mobile-friendly UI
- Deployment via Docker or cloud platforms (AWS, Azure)
- Integration with navigation apps and city dashboards
- User login and multi-user support

11. APPENDIX

- **Dataset:** traffic volume.csv
- **Notebook:** trafficIntelligence.ipynb
- **Web Pages:** index.html, output.html
- **Screenshots:** input1.png, input2.png, output.png

- **Source code:**

Index.html:

```
<!DOCTYPE html>

<html lang="en">

<head>

  <meta charset="UTF-8">

  <title>Traffic Volume Estimation</title>

  <link
href="https://cdn.jsdelivr.net/npm/bootstrap@5.3.0/dist/css/bootstrap.min.css"
rel="stylesheet">

  <style>

    body {

      background-image:
url('Traffic%20Volume%20Estimation_files/72499026.0.0.1517929277.webp');

      background-size: cover;

      background-repeat: no-repeat;

      background-position: center;

      font-family: Arial, sans-serif;

    }

    .login {

      background-color: rgba(255, 255, 255, 0.9);

      margin: 50px auto;

      padding: 40px;

      width: 50%;

      border-radius: 10px;

    }

    label {
```

```

        display: inline-block;
        width: 100px;
    }

    input, select {
        margin: 10px 0;
        padding: 6px;
        width: 200px;
    }

    .form-group {
        margin-bottom: 15px;
    }
</style>
</head>
<body>
    <div class="login">
        <h1 class="text-center">Traffic Volume Estimation</h1>
        <form action="{{ url_for('predict') }}" method="post">
            <h4>Please enter the following details</h4>

            <div class="form-group">
                <label for="holiday">Holiday:</label>
                <select id="holiday" name="holiday" required>
                    <option value="7" selected>None</option>
                    <option value="1">Columbus Day</option>
                    <option value="10">Veterans Day</option>
                    <option value="9">Thanksgiving Day</option>
                </select>
            </div>
        </form>
    </div>
</body>
</html>

```

```
<option value="0">Christmas Day</option>
<option value="6">New Year's Day</option>
<option value="11">Washington's Birthday</option>
<option value="5">Memorial Day</option>
<option value="2">Independence Day</option>
<option value="8">State Fair</option>
<option value="3">Labor Day</option>
<option value="4">Martin Luther King Jr. Day</option>
</select>
</div>
```

```
<div class="form-group">
  <label>Temp:</label>
  <input type="number" name="temp" step="0.01" required>
</div>
```

```
<div class="form-group">
  <label>Rain:</label>
  <input type="number" name="rain" min="0" max="1" step="0.01"
required>
</div>
```

```
<div class="form-group">
  <label>Snow:</label>
  <input type="number" name="snow" min="0" max="1" step="0.01"
required>
</div>
```

```
<div class="form-group">
```

```
<label for="weather">Weather:</label>
<select id="weather" name="weather" required>
  <option value="1" selected>Clouds</option>
  <option value="6">Rain</option>
  <option value="3">Drizzle</option>
  <option value="4">Haze</option>
  <option value="5">Mist</option>
  <option value="2">Fog</option>
  <option value="10">Thunderstorm</option>
  <option value="9">Snow</option>
  <option value="7">Smoke</option>
</select>
</div>

<div class="form-group">
  <label>Year:</label>
  <input type="number" name="year" min="2012" max="2022" required>
</div>

<div class="form-group">
  <label>Month:</label>
  <input type="number" name="month" min="1" max="12" required>
</div>

<div class="form-group">
  <label>Day:</label>
  <input type="number" name="day" min="1" max="31" required>
</div>
```



```

<div class="form-group">
  <label>Hours:</label>
  <input type="number" name="hours" min="0" max="23" required>
</div>

<div class="form-group">
  <label>Minutes:</label>
  <input type="number" name="minutes" min="0" max="59" required>
</div>

<div class="form-group">
  <label>Seconds:</label>
  <input type="number" name="seconds" min="0" max="59" required>
</div>

<div class="form-group text-center">
  <button type="submit" class="btn btn-primary">Predict</button>
</div>
</form>

<div class="text-center mt-4">
  <strong>{{ prediction_text }}</strong>
</div>
</div>
</body>
</html>

```

Output.html:

```
<!DOCTYPE html>

<html>

<head>

  <title>Home</title>

  <style>

    body {

      background-image: url("https://stat.overdrive.in/wp-
content/uploads/2021/10/2021-jaguar-xf-facelift-india-01.jpg");

      background-size: cover;

      margin: 0;

      padding: 0;

      font-family: 'Comic Sans MS', sans-serif;

      color: black;

    }

    .header {

      padding-bottom: 100px;

      text-align: center;

      font-size: 60px;

      font-weight: bold;

    }

    .content {

      text-align: center;

      font-size: 24px;

    }

  </style>

</head>

<body>

  <div class="header">
```

```

        Traffic volume estimation
    </div>

    <div class="content">

        <p>{{ result }}</p>

        <p>{{ prediction_text }}</p>

    </div>

</body>

</html>

```

Traffictelligence.ipynb:

%pip install numpy

Requirement already satisfied: numpy in

c:\users\diviv\appdata\local\programs\python\python313\lib\site-packages (2.2.3)

Note: you may need to restart the kernel to use updated packages.

[notice] A new release of pip is available: 24.3.1 -> 25.0.1

[notice] To update, run: python.exe -m pip install --upgrade pip

%pip install pandas

Requirement already satisfied: pandas in

c:\users\diviv\appdata\local\programs\python\python313\lib\site-packages (2.2.3)

Requirement already satisfied: numpy>=1.26.0 in

c:\users\diviv\appdata\local\programs\python\python313\lib\site-packages (from pandas)
(2.2.3)

Requirement already satisfied: python-dateutil>=2.8.2 in

c:\users\diviv\appdata\roaming\python\python313\site-packages (from pandas) (2.9.0.post0)

Requirement already satisfied: pytz>=2020.1 in

c:\users\diviv\appdata\local\programs\python\python313\lib\site-packages (from pandas)
(2025.1)

Requirement already satisfied: tzdata>=2022.7 in
c:\users\diviv\appdata\local\programs\python\python313\lib\site-packages (from pandas)
(2025.1)

Requirement already satisfied: six>=1.5 in
c:\users\diviv\appdata\roaming\python\python313\site-packages (from python-
dateutil>=2.8.2->pandas) (1.17.0)

Note: you may need to restart the kernel to use updated packages.

[notice] A new release of pip is available: 24.3.1 -> 25.0.1

[notice] To update, run: python.exe -m pip install --upgrade pip

%pip install scikit-learn

Requirement already satisfied: scikit-learn in
c:\users\diviv\appdata\local\programs\python\python313\lib\site-packages (1.6.1)

Requirement already satisfied: numpy>=1.19.5 in
c:\users\diviv\appdata\local\programs\python\python313\lib\site-packages (from scikit-learn)
(2.2.3)

Requirement already satisfied: scipy>=1.6.0 in
c:\users\diviv\appdata\local\programs\python\python313\lib\site-packages (from scikit-learn)
(1.15.2)

Requirement already satisfied: joblib>=1.2.0 in
c:\users\diviv\appdata\local\programs\python\python313\lib\site-packages (from scikit-learn)
(1.4.2)

Requirement already satisfied: threadpoolctl>=3.1.0 in
c:\users\diviv\appdata\local\programs\python\python313\lib\site-packages (from scikit-learn)
(3.5.0)

Note: you may need to restart the kernel to use updated packages.

[notice] A new release of pip is available: 24.3.1 -> 25.0.1

[notice] To update, run: python.exe -m pip install --upgrade pip

%pip install Flask

Requirement already satisfied: Flask in
c:\users\diviv\appdata\local\programs\python\python313\lib\site-packages (3.1.0)

Requirement already satisfied: Werkzeug>=3.1 in
c:\users\diviv\appdata\local\programs\python\python313\lib\site-packages (from Flask)
(3.1.3)

Requirement already satisfied: Jinja2>=3.1.2 in

c:\users\diviv\appdata\local\programs\python\python313\lib\site-packages (from Flask) (3.1.5)

Requirement already satisfied: itsdangerous>=2.2 in

c:\users\diviv\appdata\local\programs\python\python313\lib\site-packages (from Flask) (2.2.0)

Requirement already satisfied: click>=8.1.3 in

c:\users\diviv\appdata\local\programs\python\python313\lib\site-packages (from Flask) (8.1.8)

Requirement already satisfied: blinker>=1.9 in

c:\users\diviv\appdata\local\programs\python\python313\lib\site-packages (from Flask) (1.9.0)

Requirement already satisfied: colorama in

c:\users\diviv\appdata\roaming\python\python313\site-packages (from click>=8.1.3->Flask) (0.4.6)

Requirement already satisfied: MarkupSafe>=2.0 in

c:\users\diviv\appdata\local\programs\python\python313\lib\site-packages (from Jinja2>=3.1.2->Flask) (3.0.2)

Note: you may need to restart the kernel to use updated packages.

[notice] A new release of pip is available: 24.3.1 -> 25.0.1

[notice] To update, run: python.exe -m pip install --upgrade pip

%pip install xgboost

Requirement already satisfied: xgboost in

c:\users\diviv\appdata\local\programs\python\python313\lib\site-packages (2.1.4)

Requirement already satisfied: numpy in

c:\users\diviv\appdata\local\programs\python\python313\lib\site-packages (from xgboost) (2.2.3)

Requirement already satisfied: scipy in

c:\users\diviv\appdata\local\programs\python\python313\lib\site-packages (from xgboost) (1.15.2)

Note: you may need to restart the kernel to use updated packages.

[notice] A new release of pip is available: 24.3.1 -> 25.0.1

[notice] To update, run: python.exe -m pip install --upgrade pip

%pip install seaborn

Requirement already satisfied: seaborn in
c:\users\diviv\appdata\local\programs\python\python313\lib\site-packages (0.13.2)

Requirement already satisfied: numpy!=1.24.0,>=1.20 in
c:\users\diviv\appdata\local\programs\python\python313\lib\site-packages (from seaborn)
(2.2.3)

Requirement already satisfied: pandas>=1.2 in
c:\users\diviv\appdata\local\programs\python\python313\lib\site-packages (from seaborn)
(2.2.3)

Requirement already satisfied: matplotlib!=3.6.1,>=3.4 in
c:\users\diviv\appdata\local\programs\python\python313\lib\site-packages (from seaborn)
(3.10.1)

Requirement already satisfied: contourpy>=1.0.1 in
c:\users\diviv\appdata\local\programs\python\python313\lib\site-packages (from
matplotlib!=3.6.1,>=3.4->seaborn) (1.3.1)

Requirement already satisfied: cycler>=0.10 in
c:\users\diviv\appdata\local\programs\python\python313\lib\site-packages (from
matplotlib!=3.6.1,>=3.4->seaborn) (0.12.1)

Requirement already satisfied: fonttools>=4.22.0 in
c:\users\diviv\appdata\local\programs\python\python313\lib\site-packages (from
matplotlib!=3.6.1,>=3.4->seaborn) (4.56.0)

Requirement already satisfied: kiwisolver>=1.3.1 in
c:\users\diviv\appdata\local\programs\python\python313\lib\site-packages (from
matplotlib!=3.6.1,>=3.4->seaborn) (1.4.8)

Requirement already satisfied: packaging>=20.0 in
c:\users\diviv\appdata\roaming\python\python313\site-packages (from
matplotlib!=3.6.1,>=3.4->seaborn) (24.2)

Requirement already satisfied: pillow>=8 in
c:\users\diviv\appdata\local\programs\python\python313\lib\site-packages (from
matplotlib!=3.6.1,>=3.4->seaborn) (11.1.0)

Requirement already satisfied: pyparsing>=2.3.1 in
c:\users\diviv\appdata\local\programs\python\python313\lib\site-packages (from
matplotlib!=3.6.1,>=3.4->seaborn) (3.2.1)

Requirement already satisfied: python-dateutil>=2.7 in
c:\users\diviv\appdata\roaming\python\python313\site-packages (from
matplotlib!=3.6.1,>=3.4->seaborn) (2.9.0.post0)

Requirement already satisfied: pytz>=2020.1 in
c:\users\diviv\appdata\local\programs\python\python313\lib\site-packages (from
pandas>=1.2->seaborn) (2025.1)

Requirement already satisfied: tzdata>=2022.7 in
c:\users\diviv\appdata\local\programs\python\python313\lib\site-packages (from
pandas>=1.2->seaborn) (2025.1)

Requirement already satisfied: six>=1.5 in
c:\users\diviv\appdata\roaming\python\python313\site-packages (from python-dateutil>=2.7-
>matplotlib!=3.6.1,>=3.4->seaborn) (1.17.0)

Note: you may need to restart the kernel to use updated packages.

[notice] A new release of pip is available: 24.3.1 -> 25.0.1

[notice] To update, run: python.exe -m pip install --upgrade pip

Importing the necessary libraries

Importing the necessary libraries

import pandas as pd

import numpy as np

import seaborn as sns

from sklearn **import** linear_model

from sklearn **import** tree

from sklearn **import** ensemble

from sklearn **import** svm

import xgboost

Importing the Dataset

data = pd.read_csv('traffic volume.csv')

Analyse The Data

data.head()

	holiday	temp	rain	snow	weather	date	Time	traffic_volume
0	NaN	288.28	0.0	0.0	Clouds	02-10-2012	09:00:00	5545

	holiday	temp	rain	snow	weather	date	Time	traffic_volume
1	NaN	289.36	0.0	0.0	Clouds	02-10-2012	10:00:00	4516
2	NaN	289.58	0.0	0.0	Clouds	02-10-2012	11:00:00	4767
3	NaN	290.13	0.0	0.0	Clouds	02-10-2012	12:00:00	5026
4	NaN	291.14	0.0	0.0	Clouds	02-10-2012	13:00:00	4918

data.describe()

	temp	rain	snow	traffic_volume
count	48151.000000	48202.000000	48192.000000	48204.000000
mean	281.205351	0.334278	0.000222	3259.818355
std	13.343675	44.790062	0.008169	1986.860670
min	0.000000	0.000000	0.000000	0.000000
25%	272.160000	0.000000	0.000000	1193.000000
50%	282.460000	0.000000	0.000000	3380.000000
75%	291.810000	0.000000	0.000000	4933.000000
max	310.070000	9831.300000	0.510000	7280.000000

data.info()

<class 'pandas.core.frame.DataFrame'>

RangeIndex: 48204 entries, 0 to 48203

Data columns (total 8 columns):

#	Column	Non-Null Count	Dtype
---	--------	----------------	-------

---	-----	-----	-----
-----	-------	-------	-------


```
0 holiday      61 non-null  object
1 temp        48151 non-null float64
2 rain        48202 non-null float64
3 snow        48192 non-null float64
4 weather     48155 non-null object
5 date        48204 non-null object
6 Time        48204 non-null object
7 traffic_volume 48204 non-null int64
```

```
dtypes: float64(3), int64(1), object(4)
```

```
memory usage: 2.9+ MB
```

Handling Missing Values

```
data.isnull().sum()
```

```
holiday      48143
temp         53
rain         2
snow        12
weather      49
date         0
Time         0
traffic_volume 0
```

```
dtype: int64
```

```
data['temp'].fillna(data['temp'].mean())
```

```
data['rain'].fillna(data['rain'].mean())
```

```
data['snow'].fillna(data['snow'].mean())
```

```
0    0.0
1    0.0
2    0.0
3    0.0
```

```
4      0.0
...
48199  0.0
48200  0.0
48201  0.0
48202  0.0
48203  0.0
```

Name: snow, Length: 48204, dtype: float64

```
from collections import Counter
```

```
print(Counter(data['weather']))
```

```
Counter({'Clouds': 15144, 'Clear': 13383, 'Mist': 5942, 'Rain': 5665, 'Snow': 2875, 'Drizzle': 1818, 'Haze': 1359, 'Thunderstorm': 1033, 'Fog': 912, 'nan': 49, 'Smoke': 20, 'Squall': 4})
```

Data Visualization

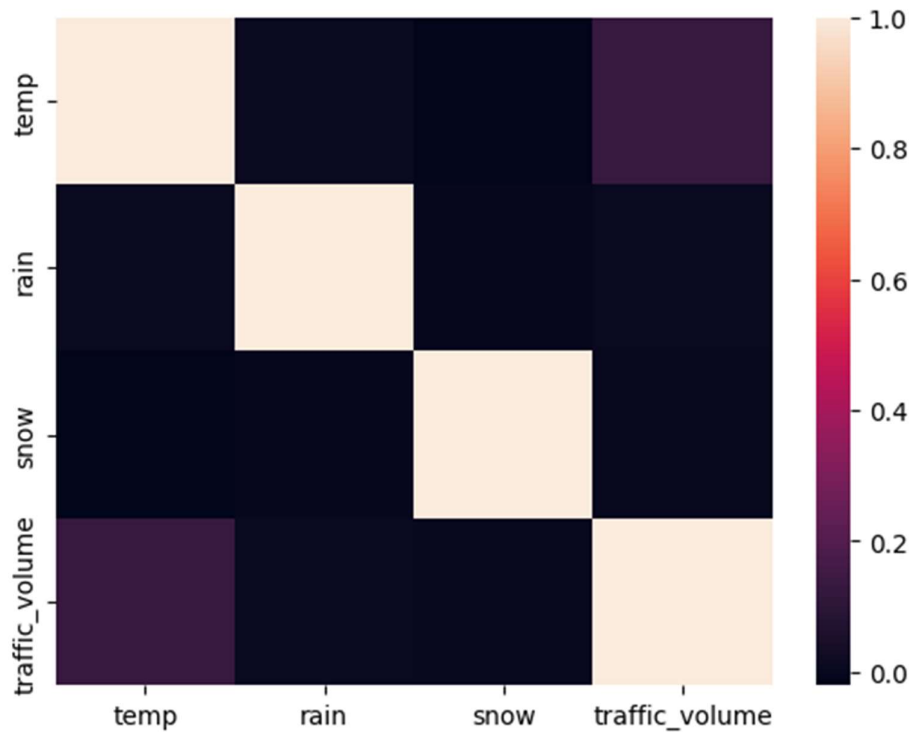
```
data.corr
```

```
data = data.select_dtypes(include=["number"]) # Keep only numeric columns
```

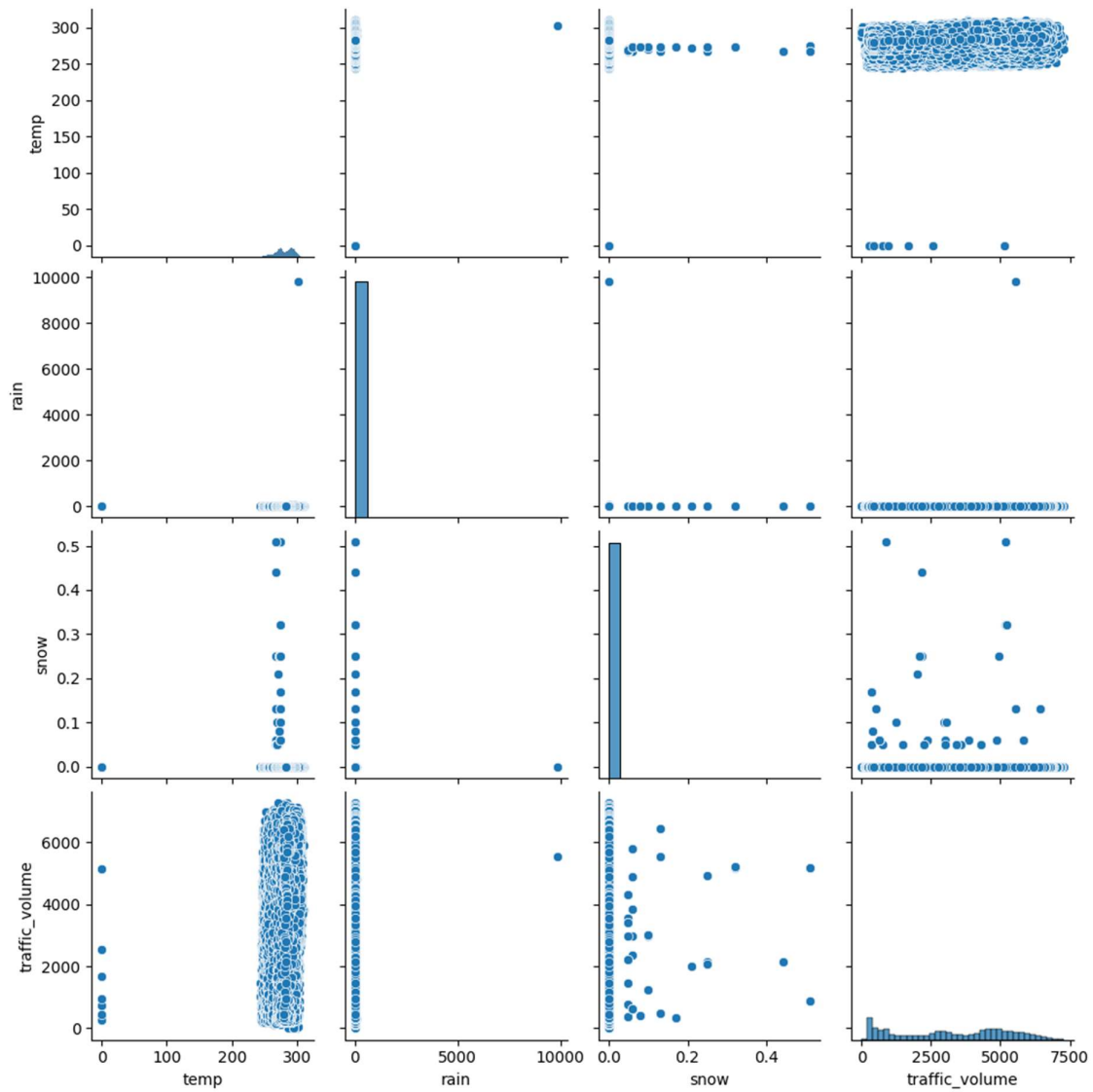
```
corr = data.corr() # Correct
```

```
sns.heatmap(corr)
```

```
<Axes: >
```

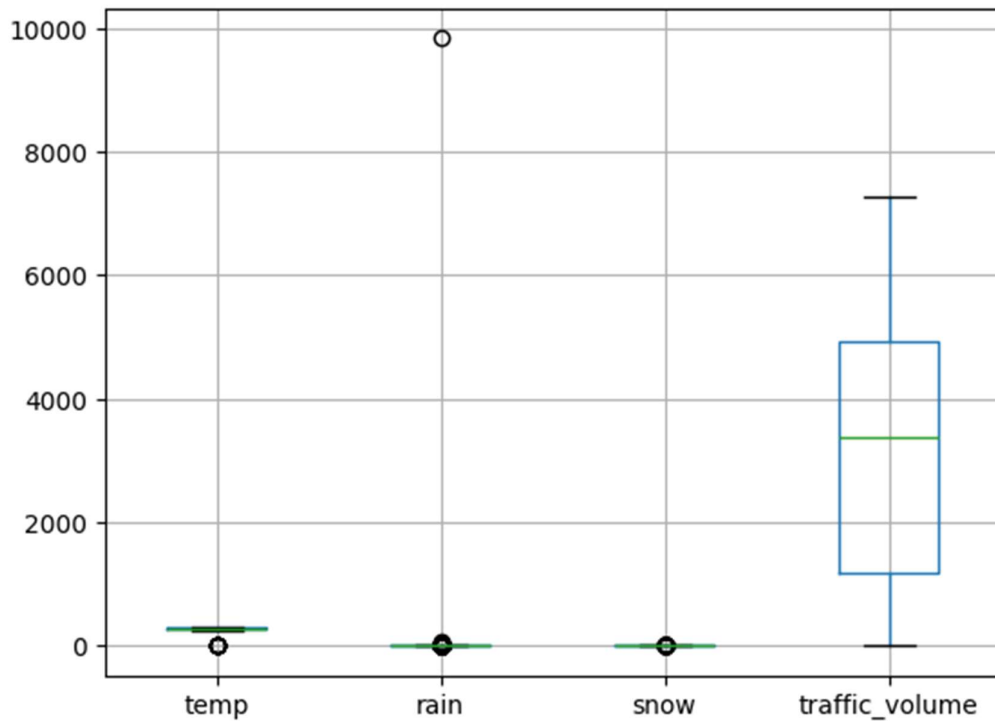


```
import pandas as pd
data = pd.read_csv('traffic volume.csv')
sns.pairplot(data)
<seaborn.axisgrid.PairGrid at 0x1efa8067e00>
```



```
data.boxplot()
```

```
<Axes: >
```



```
from sklearn.preprocessing import LabelEncoder
```

```
le = LabelEncoder()
```

```
data['weather'] = le.fit_transform(data['weather'])
```

```
data.head()
```

	holiday	temp	rain	snow	weather	date	Time	traffic_volume
0	NaN	288.28	0.0	0.0	1	02-10-2012	09:00:00	5545
1	NaN	289.36	0.0	0.0	1	02-10-2012	10:00:00	4516
2	NaN	289.58	0.0	0.0	1	02-10-2012	11:00:00	4767
3	NaN	290.13	0.0	0.0	1	02-10-2012	12:00:00	5026
4	NaN	291.14	0.0	0.0	1	02-10-2012	13:00:00	4918

```
data['temp'] = le.fit_transform(data['temp'])
```

```
data[["day", "month", "year"]] = data["date"].str.split("-", expand=True)
```

```
data[["hours", "minutes", "seconds"]] = data["Time"].str.split(":", expand=True)
```

```
data.drop(columns=['date', 'Time'], axis=1, inplace=True)
```

```
data.head()
```

	holiday	temp	rain	snow	windy	traffic_volume	day	month	year	hours	minutes	seconds
0	NaN	4025	0.0	0.0	1	5545	02	10	2012	09	00	00
1	NaN	4145	0.0	0.0	1	4516	02	10	2012	10	00	00
2	NaN	4168	0.0	0.0	1	4767	02	10	2012	11	00	00
3	NaN	4229	0.0	0.0	1	5026	02	10	2012	12	00	00
4	NaN	4346	0.0	0.0	1	4918	02	10	2012	13	00	00

Splitting the Dataset into Dependent and Independent variable

```
import pandas as pd
```

```
from sklearn.preprocessing import LabelEncoder, StandardScaler
```

```
y = data.drop(columns=['traffic_volume'], axis=1)
```

```
x = data.drop(columns=['traffic_volume'], axis=1)
```

Feature Scaling

```
names = x.columns
```

```
x = pd.DataFrame(x, columns = names)
```

```
x = pd.DataFrame(y, columns= names) # Ensure correct column name
```

```
x.head()
```

	holida y	tem p	rai n	sno w	weathe r	da y	mont h	yea r	hour s	minute s	second s
0	NaN	402 5	0.0	0.0	1	02	10	201 2	09	00	00
1	NaN	414 5	0.0	0.0	1	02	10	201 2	10	00	00
2	NaN	416 8	0.0	0.0	1	02	10	201 2	11	00	00
3	NaN	422 9	0.0	0.0	1	02	10	201 2	12	00	00
4	NaN	434 6	0.0	0.0	1	02	10	201 2	13	00	00

Define Features and Target Variable

`x = data.drop(columns=['traffic_volume'])` *# Features*

`y = data['traffic_volume']` *# Target*

`x.shape`

`(48204, 11)`

`y.shape`

`(48204,)`

`print(x.dtypes)`

holiday object

temp int64

rain float64

snow float64

weather int64

day object

month object

```
year    object
hours   object
minutes object
seconds object
```

```
dtype: object
```

Splitting the data into Train and Test

```
from sklearn.model_selection import train_test_split
```

```
from sklearn.preprocessing import LabelEncoder
```

```
categorical_columns = ['holiday', 'temp', 'rain', 'snow', 'weather', 'year', 'month', 'day', 'hours',  
'minutes', 'seconds']
```

```
label_encoders = {}
```

```
for col in categorical_columns:
```

```
    le = LabelEncoder()
```

```
    x[col] = le.fit_transform(x[col]) # Convert categorical to numeric
```

```
    label_encoders[col] = le # Store encoders for later use
```

```
# Splitting dataset into training and testing sets
```

```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=0)
```

```
x_train.shape
```

```
(38563, 11)
```

Model Building

Training and Testing the Model

```
# Model Initializations
```

```
lin_reg = linear_model.LinearRegression()
```

```
Dtree = tree.DecisionTreeRegressor()
```

```
Rand = ensemble.RandomForestRegressor(n_estimators=100, random_state=42)
```

```
svr = svm.SVR()
```

```
XGB = xgboost.XGBRegressor()
```

```
print(x_train.isnull().sum()) # Check for missing values in each column
```

```
print(y_train.isnull().sum()) # Check for missing values in target variable
```



```
holiday  0
temp     0
rain     0
snow     0
weather  0
day       0
month    0
year     0
hours    0
minutes  0
seconds  0
dtype: int64
0
```

```
from sklearn.impute import SimpleImputer
```

```
imputer = SimpleImputer(strategy="mean") # Options: "median", "most_frequent"
```

```
x_train = imputer.fit_transform(x_train) # Fills missing values with mean
```

```
x_test = imputer.transform(x_test)
```

```
# Train models
```

```
lin_reg.fit(x_train, y_train)
```

```
Dtree.fit(x_train, y_train)
```

```
Rand.fit(x_train, y_train)
```

```
svr.fit(x_train, y_train)
```

```
XGB.fit(x_train, y_train)
```

```
XGBRegressor(base_score=None, booster=None, callbacks=None,  
              colsample_bylevel=None, colsample_bynode=None,  
              colsample_bytree=None, device=None, early_stopping_rounds=None,  
              enable_categorical=False, eval_metric=None, feature_types=None,
```

```
gamma=None, grow_policy=None, importance_type=None,  
interaction_constraints=None, learning_rate=None, max_bin=None,  
max_cat_threshold=None, max_cat_to_onehot=None,  
max_delta_step=None, max_depth=None, max_leaves=None,  
min_child_weight=None, missing=nan, monotone_constraints=None,  
multi_strategy=None, n_estimators=None, n_jobs=None,  
num_parallel_tree=None, random_state=None, ...)
```

```
p1 = lin_reg.predict(x_train)
```

```
p2 = Dtree.predict(x_train)
```

```
p3 = Rand.predict(x_train)
```

```
p4 = svr.predict(x_train)
```

```
p5 = XGB.predict(x_train)
```

Model Evaluation

```
from sklearn import metrics
```

```
print(metrics.r2_score(p1, y_train))
```

```
print(metrics.r2_score(p2, y_train))
```

```
print(metrics.r2_score(p3, y_train))
```

```
print(metrics.r2_score(p4, y_train))
```

```
print(metrics.r2_score(p5, y_train))
```

```
-5.45898314059456
```

```
1.0
```

```
0.9747230692401472
```

```
-58.11845129400455
```

```
0.8460580706596375
```

```
x_train = np.nan_to_num(x_train, nan=np.nanmean(x_train))
```

```
x_test = np.nan_to_num(x_test, nan=np.nanmean(x_test))
```

```
p1 = lin_reg.predict(x_test)
```

```
p2 = Dtree.predict(x_test)
```

```

p3 = Rand.predict(x_test)
p4 = svr.predict(x_test)
p5 = XGB.predict(x_test)
print(metrics.r2_score(p1, y_test))
print(metrics.r2_score(p2, y_test))
print(metrics.r2_score(p3, y_test))
print(metrics.r2_score(p4, y_test))
print(metrics.r2_score(p5, y_test))
-5.326830630340053
0.6833687058990447
0.8019717048784262
-56.8140817039808
0.8068752288818359
RMSE –Root Mean Square Error
from sklearn.metrics import mean_squared_error
MSE = mean_squared_error(p3, y_test)
np.sqrt(MSE)
np.float64(800.7602451294027)
import pickle
from sklearn.ensemble import RandomForestRegressor
model = RandomForestRegressor(n_estimators=100, random_state=42)
model.fit(x_train, y_train)
RandomForestRegressor(random_state=42)

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

scaler = StandardScaler()
x_scaled = scaler.fit_transform(x_test) # Fit on the current dataset

```

```
pickle.dump(model, open("model.pkl", "wb"))  
pickle.dump(scaler, open("encoder.pkl", "wb"))
```

Dataset Link:

https://drive.google.com/file/d/1iV5PfYAmI6YP0_0S4KYy1ZahHOqMgDbM/view

GitHub & Project Demo Link

- GitHub:
- Demo: