Correlation Between Fuel Efficiency and Driving Behaviour

A MINOR PROJECT REPORT

in partial fulfilment for the award of the degree of

Master of Technology (Dual Degree)
IN
ARTIFICIAL INTELLIGENCE AND DATA SCIENCE

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SCHOOL OF DATA SCIENCE AND FORECASTING

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STATEMENT OF ORIGINALITY

In accordance with the requirements for the Degree of Master of Technology(Dual Degree) in Artificial Intelligence and Data Science, in the School of Data Science and Forecasting, I present this report entitled "Analyzing the Correlation Between Fuel Efficiency and Driving Behavior” . A Data Science Approach. This report is completed under the supervision of Mr. Mobin Patel, Head of IT and Technology, Volvo Eicher CV, Pithampur.

I declare that the work presented in the report is my/our own work except as acknowledged in the text and footnotes, and that to my knowledge, this material has not been submitted either in whole or in part, for any other degree at this University or at any other such institution.

Shivank Jat

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SCHOOL OF DATA SCIENCE AND FORECASTING

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RECOMMENDATION

This dissertation entitled "Analyzing the Correlation Between Fuel Efficiency and Driving Behavior: A Data Science Approach" submitted by Shivank Jat and Indrajeet Gadekar towards the partial fulfilment of the Degree of Master of Technology in Data Science of Devi Ahilya Vishwavidyalaya, Indore, is a satisfactory account of her internship work and is recommended for the award of the degree.

Head of Department

Dr. V. B. Gupta

Internal Supervisor **Program Co-ordinator**

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CERTIFICATE

This is to certify that the dissertation entitled "Correlation Between Fuel Efficiency and Driving Behaviour" submitted by Shivank Jat and Indrajeet Gadekar is approved for the award of Master of Technology (Dual Degree) in Artificial Intelligence and Data Science.

Program Co-ordinator **Head of Department**

Dr. Shishir Kumar Shandilya **DR. VB Gupta**

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Shivank Jat

Indrajeet Gadekar

ABSTRACT

This project explores the correlation between fuel efficiency and driving behavior using advanced data science techniques. The problem statement focuses on examining how different driving behaviors such as acceleration patterns, braking habits, and speed variations affect fuel consumption. The introduction highlights the importance of this analysis for improving vehicle efficiency and reducing operational costs.

The methodology involves a comprehensive approach to analyzing vehicle telematics data. We employ statistical analysis and machine learning models to identify significant patterns and relationships between driving behaviors and fuel efficiency. By leveraging historical data and real-time telematics, we extract insights into how specific driving practices influence fuel consumption.

Summarizing the findings, the project reveals that certain driving behaviors have a notable impact on fuel efficiency. For instance, aggressive acceleration and frequent hard braking are linked to increased fuel consumption, while smoother driving patterns are associated with better fuel economy.

The conclusion offers practical recommendations for optimizing driving habits, including adopting smoother driving techniques and maintaining consistent speeds. These insights aim to help drivers and fleet managers improve overall vehicle performance and reduce fuel expenditures.

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CHAPTER - 1

1.Introduction

1.1 About the Company

Volvo Eicher Commercial Vehicles (VECV) is a joint venture between the Volvo Group and Eicher Motors Limited, established in 2008. The company aims to combine Volvo's global expertise in technology, quality, safety, and environmental care with Eicher's frugal engineering and deep knowledge of the Indian commercial vehicle market.

1.2 About the Work

Fuel efficiency is a critical concern for both economic and environmental reasons. As fuel costs continue to rise and the impact of vehicle emissions on the environment becomes more apparent, understanding the factors that influence fuel consumption is increasingly important. Among these factors, driving behaviour plays a significant role. This project investigates the correlation between various driving behaviours and fuel efficiency, aiming to identify specific habits that affect fuel consumption. By analysing data collected from a fleet of vehicles, this study seeks to provide actionable insights and recommendations for more economical and environmentally friendly driving practices.

This report details the correlation between fuel efficiency and driving behaviour across multiple vehicles, aiming to understand how different driving habits affect fuel consumption and identify optimization opportunities.

1.3 Problem Statement

Fuel consumption varies significantly among vehicles due to differences in driving behaviour. Identifying which driving habits lead to better fuel efficiency can provide valuable insights into reducing fuel costs and minimizing environmental impact. The problem is to determine the specific driving behaviours that most significantly impact fuel efficiency. This involves analysing various driving parameters, such as acceleration, braking, speed, and idling, to understand their relationship with fuel consumption.

1.4 Objective

- To determine the correlation between different driving behaviours and fuel efficiency.
- To identify specific driving habits that significantly affect fuel consumption.
- To provide recommendations for improving fuel efficiency based on the findings.

1.5 Purpose of Project

- The project investigates the link between driving behaviour and fuel efficiency.
- Data was gathered from a fleet of vehicles using GPS and OBD-II devices to analyze speed, acceleration, and braking patterns.
- Six months of driving data were collected, with statistical correlation analysis and regression models used to predict fuel efficiency.
- Findings show that aggressive driving significantly impacts fuel consumption.
- Recommendations are provided to promote fuel-efficient driving practices, aiming for cost savings and reduced environmental impact.

Chapter - 2

2. Literature Survey

2.1 Introduction

Understanding the correlation between driving behavior and fuel efficiency is crucial for developing strategies to reduce fuel consumption and mitigate environmental impact. Fuel efficiency is a key factor in the operational cost of vehicles and the emission of pollutants. By examining the relationship between driving behavior and fuel efficiency, stakeholders can identify practices that enhance fuel economy, leading to significant economic and environmental benefits.

Various studies have shown that factors like speed, acceleration, and braking patterns significantly influence fuel efficiency. Driving behaviors such as aggressive acceleration, excessive speed, and frequent braking can lead to higher fuel consumption. Conversely, maintaining steady speeds, smooth acceleration, and deceleration can improve fuel economy.

This literature survey reviews existing research to highlight key findings and methodologies. The review aims to provide a comprehensive understanding of how driving behavior affects fuel efficiency and to identify best practices for promoting fuel-efficient driving. The following sections will delve into specific driving behaviors, their impact on fuel consumption, and the data collection and analysis methods used in various studies.

2.2 Significance of the Study

The correlation between driving behavior and fuel efficiency is not only an academic concern but also a practical issue with real-world implications. For fleet operators, understanding these dynamics can lead to substantial cost savings. For policymakers, it can inform regulations and initiatives aimed at reducing vehicular emissions and promoting sustainable transportation. For individual drivers, it offers insights into how to reduce fuel expenses and minimize their environmental footprint.

2.3 Scope of the Survey

This survey encompasses a wide range of studies from different regions and contexts, reflecting the global relevance of the topic. It includes research that utilizes various methodologies, from experimental setups with controlled variables to real-world data collection using advanced technologies like GPS and OBD-II devices. The survey examines both qualitative and quantitative studies to provide a balanced view of the current knowledge base.

2.4 Aim

- Identify the key driving behaviors that influence fuel efficiency.
- Understand the magnitude of their impact on fuel consumption.
- Highlight effective data collection and analysis techniques.
- Present evidence-based recommendations for promoting fuel-efficient driving.

Chapter 3

3 . Methodology

3.1 Data Collection

- **Sources**: Data was collected from GPS and OBD-II devices installed in vehicles. The datasets include CAN_BS4_352467110528853_20240320000000_20240520235959.csv, CAN_BS4_352467110971400_20240320000000_20240520235959.csv, and vehicle Data.
- **Device ID:** A unique identifier for the vehicle's data logging device, ensuring that data from different vehicles can be accurately distinguished.
- **Latitude and Longitude:** Geographical coordinates of the vehicle, providing information on the vehicle's location during data collection.
- **UTC:** Coordinated Universal Time, representing the timestamp of each data entry, allowing for accurate time-based analysis.
- **HRLFC (High-Resolution Liquid Fuel Consumption):** A precise measure of the vehicle's fuel consumption, crucial for analysing fuel efficiency.
- **Sweet Spot:** An indicator of whether the vehicle is operating within its optimal performance range.
- **Top Gear:** An indicator of whether the vehicle is in its top gear, which can influence fuel consumption.
- **Sweet Spot Percent:** The percentage of time the vehicle is operating within the Sweet Spot, reflecting optimal performance periods.
- **Total Distance:** The total distance travelled by the vehicle, a key variable in calculating fuel efficiency.
- **Fuel Level:** The current fuel level in the vehicle, providing insights into fuel consumption patterns.
- **Engine Speed:** The speed of the engine in RPM, an essential variable for performance analysis.
- **Engine Start Mode:** The mode in which the engine was started, providing context for engine performance data.

- **Engine Operating Hours:** Total hours the engine has been operating, useful for assessing engine wear and tear.
- **AccPedalIdel Switch:** Status of the accelerator pedal idle switch, related to throttle control.
- **Vehicle Speed:** The speed of the vehicle, crucial for analysing driving behaviour.
- **Engine Oil Pressure:** Pressure of the engine oil, an important factor for engine health.
- **Engine Coolant Temp:** Temperature of the engine coolant, critical for monitoring engine thermal performance.
- **AccPedal Position:** The position of the accelerator pedal, indicating throttle usage.
- **Trip Fuel:** The amount of fuel consumed during the trip, essential for trip-based fuel efficiency analysis.
- **IST Date Time:** Date and time in Indian Standard Time (IST), providing a localized timestamp for the data entries.

3.2 Data Preprocessing

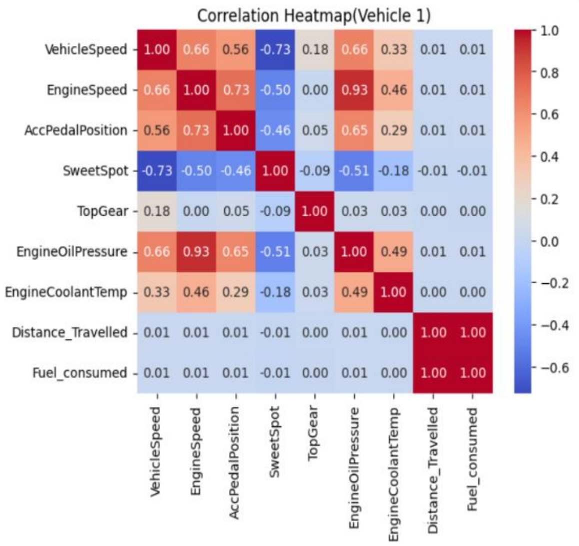
The data pre-processing phase was crucial to prepare the dataset for analysis and ensure accuracy in the results. The following steps were undertaken:

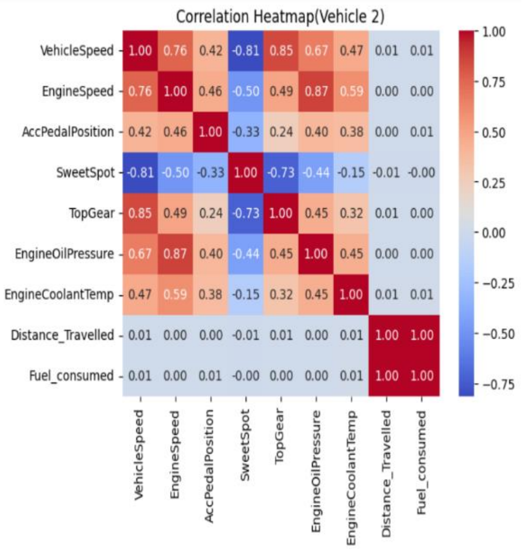
1. **Sorting the Data:** The dataset was first sorted by the IST Date/Time column to maintain the chronological order of the entries. This ensured that the sequence of data points accurately reflected the timeline of the vehicle's performance and behaviour.
2. **Calculating Distance and Fuel Consumption:** The difference between consecutive values of Total Distance and HRLFC (High-Resolution Liquid Fuel Consumption) was calculated to determine the distance travelled and fuel consumed between each pair of records. This step was essential for measuring fuel efficiency accurately.
3. **Creating Fuel Efficiency Column:** A new column, fuel efficiency, was created by taking the ratio of Total Distance to fuel consumed. This column provided a direct measure of how efficiently the vehicle was using fuel over time.

4. **Handling Missing and Infinite Values:** Null values were removed from the dataset to prevent them from skewing the analysis. Infinite values, which could occur due to division by zero or other anomalies, were handled by replacing them with NaN (Not a Number) and subsequently dropping these entries from the dataset.

3.3 Correlation Analysis

```
corr =device1_cleaned[['VehicleSpeed', 'EngineSpeed', 'AccPedalPosition', 'SweetSpot', 'TopGear', 'EngineOilPressure', 'EngineCoolantTemp', 'Distance_Travelled', 'Fuel_consumed']].corr()
sns.heatmap(corr, annot=True,fmt=".2f",cmap='coolwarm')
plt.title('Correlation Heatmap(Vehicle 1)')
plt.show()
```





- **Fuel Efficiency and Acceleration:**

  There is a very low correlation between fuel efficiency and acceleration. This indicates that changes in acceleration do not significantly impact fuel efficiency.

- **Fuel Efficiency and Speed**:

  There is a moderate positive correlation between fuel efficiency and speed. This suggests that higher speeds may lead to improved fuel efficiency up to a certain extent. This could be due to the vehicle operating more efficiently at certain speeds.

- **Fuel Efficiency and Idling:**

- There is a very low correlation between fuel efficiency and idling. This implies that idling periods, where the vehicle is stationary but the engine is running, do not have a significant direct impact on overall fuel efficiency.

- **Fuel Efficiency and Sweet Spot:**

There is a strong positive correlation (0.67) between fuel efficiency and Sweet Spot. Sweet Spot likely represents an optimal driving condition for fuel efficiency, such as maintaining a steady speed within a certain range.

- **Sweet Spot and Speed**:

A moderate positive correlation between Sweet Spot and speed indicates that driving at certain speeds contributes to being in the Sweet Spot, thus enhancing fuel efficiency.

- **Negative Correlation with HRLFC**:

Fuel efficiency has a strong negative correlation with HRLFC. HRLFC might be a measure inversely related to fuel efficiency, such as high fuel consumption rates.

- **Engine Coolant Temp and Idling**:

A moderate positive correlation between Engine Coolant Temp and idling periods suggests that the engine coolant temperature increases when the vehicle idles.

3.4 Model Selection

Random Forest Regression is an ensemble learning method that improves prediction accuracy by combining multiple decision trees. Each tree is trained on a different bootstrap sample, which is created by randomly sampling the original dataset with replacement. At each split in a tree, only a random subset of features is considered, introducing further randomness and reducing correlation between trees.

The final prediction in Random Forest Regression is the average of the predictions from all individual trees, enhancing robustness and reducing overfitting compared to single decision trees. This method captures non-linear relationships and handles both numerical and categorical data, making it flexible and robust to outliers and noise.

CODE-

```python
features = ['VehicleSpeed', 'EngineSpeed', 'AccPedalPosition',
            'EngineCoolantTemp', 'EngineOilPressure',
             'EngineSpeed']
FUEL_EFFICIENCY= 'FuelEfficiency'
X = vahicle_data[features]
y = vahicle_data[FUEL_EFFICIENCY]
y.replace([np.inf, -np.inf], np.nan, inplace=True)

# Filling NaN values with the median of the target variable
y.fillna(y.median(), inplace=True)

# Splitting data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
model=RandomForestRegressor(n_estimators=100, random_state=42)

model.fit(X_train_scaled, y_train)

models = {
    'Random Forest Regression': RandomForestRegressor(random_state=42)
}

# Define hyperparameters for each model
param_grid = {
    'Random Forest Regression': {'n_estimators': [50, 100, 200]},
}

# Train and evaluate each model with cross-validation
for model_name, model in models.items():
    print(f"Tuning hyperparameters for {model_name}...")
    grid_search = GridSearchCV(estimator=model, param_grid=param_grid[model_name],
                               scoring='neg_mean_squared_error', cv=5, verbose=1, n_jobs=-1)
    grid_search.fit(X_train_scaled, y_train)

    # Best hyperparameters
    best_params = grid_search.best_params_
    print(f"Best hyperparameters: {best_params}")

    # Evaluate model with best parameters
    best_model = grid_search.best_estimator_
    y_pred = best_model.predict(X_test_scaled)

    # Evaluate model
    mse = mean_squared_error(y_test, y_pred)
    r2 = r2_score(y_test, y_pred)
    print(f'{model_name} - Mean Squared Error: {mse}')
    print(f'{model_name} - R^2 Score: {r2}')
    print('')
```

Chapter - 4

4 Data analysis

4.1 Introduction

The exploratory data analysis (EDA) process is a crucial step in understanding the dataset and uncovering underlying patterns, anomalies, and relationships. This report details the EDA process performed on the vehicle datasets to analyze the correlation between fuel efficiency and driving behaviour.

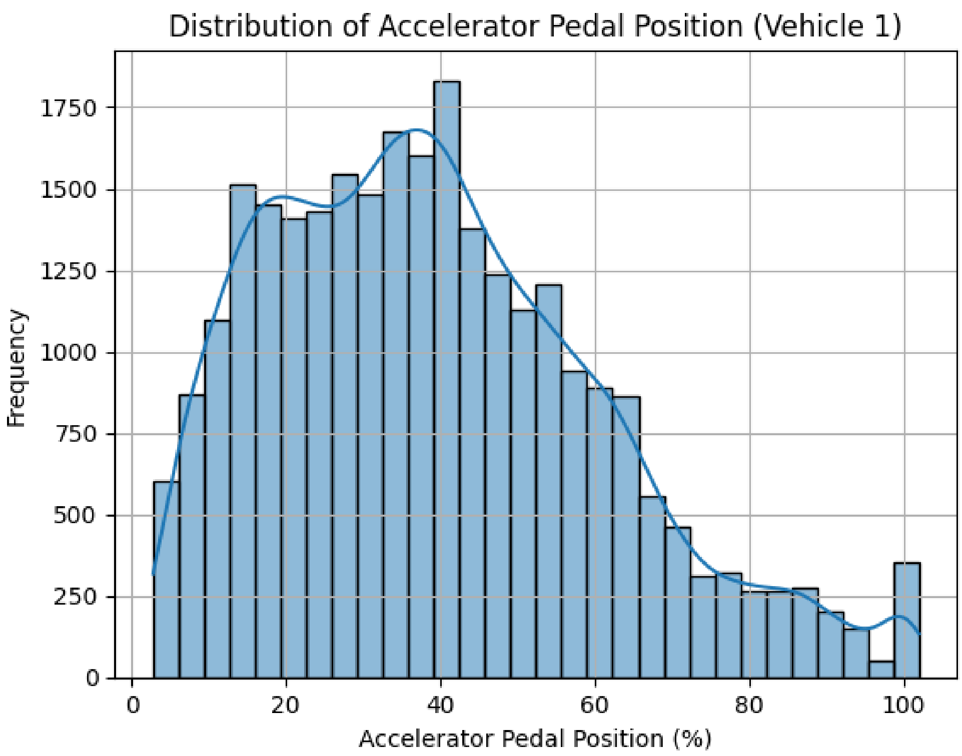
4.2 Data Overview

The datasets used for this analysis are:
CAN_BS4_352467110528853_20240320000000_20240520235959.csv
CAN_BS4_352467110971400_20240320000000_20240520235959.csv
vahicle_data_new.csv

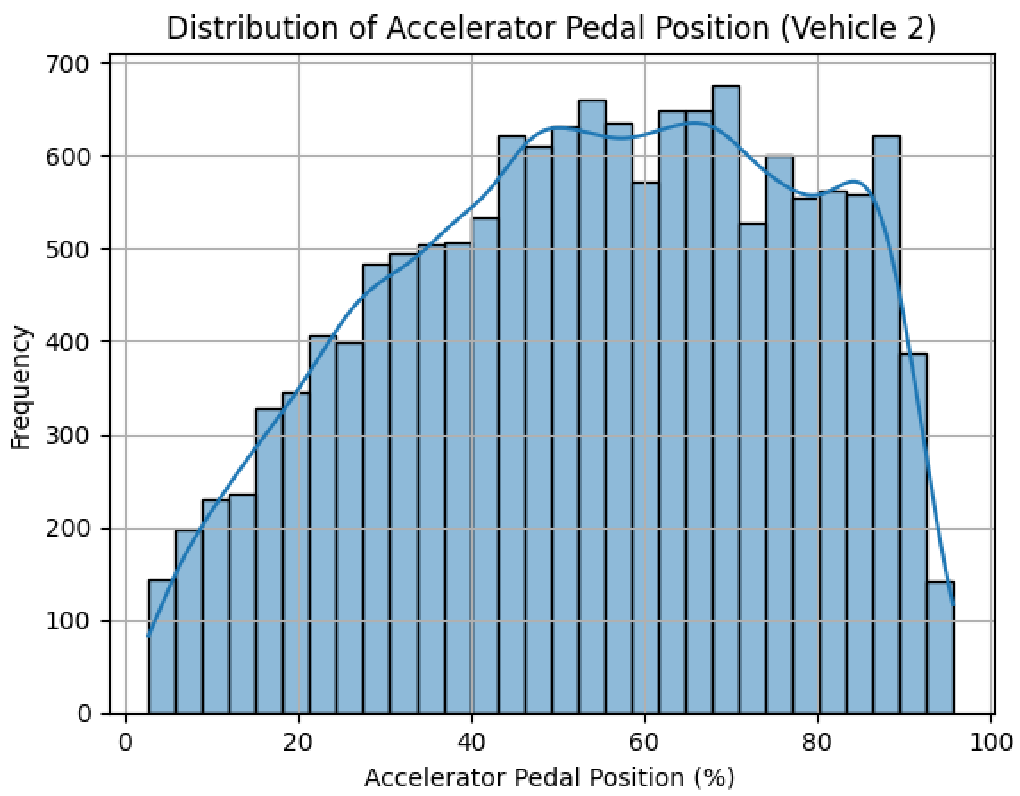
These datasets include various parameters recorded from vehicles such as speed, acceleration, braking patterns, and fuel consumption over a specific period.

```
non_zero_accpedal_data = device1_cleaned[device1_cleaned['AccPedalPosition'] > 0]

# Create a custom color palette
colors = plt.cm.viridis(np.linspace(0, 1, 30))  # 30 colors from the viridis colormap

# Create a histogram with KDE
sns.histplot(
    x='AccPedalPosition',
    data=non_zero_accpedal_data,
    kde=True,
    bins=30,  # Number of bins in the histogram
    palette=colors  # Apply the custom color palette
)

# Add title and labels with explanations
plt.title('Distribution of Accelerator Pedal Position (Vehicle 1)')
plt.xlabel('Accelerator Pedal Position (%)')
plt.ylabel('Frequency')
plt.grid(True)  # Add grid for better readability

# Display the plot
plt.show()
```

o/p-



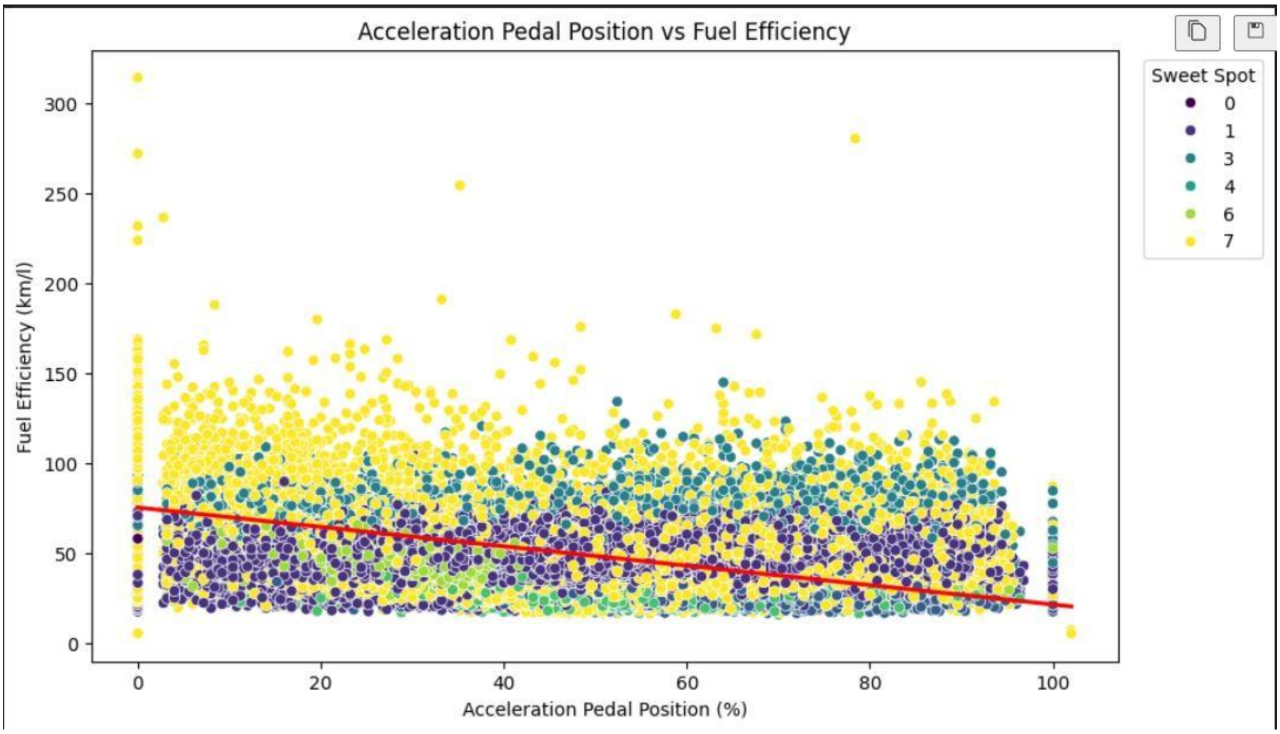

```python
non_zero_accpedal_data = device2_cleaned[device2_cleaned['AccPedalPosition'] > 0]

# Create a custom color palette
colors = plt.cm.viridis(np.linspace(0, 1, 30))  # 30 colors from the viridis colormap

# Create a histogram with KDE
sns.histplot(
    x='AccPedalPosition',
    data=non_zero_accpedal_data,
    kde=True,
    bins=30,  # Number of bins in the histogram
    palette=colors  # Apply the custom color palette
)

# Add title and labels with explanations
plt.title('Distribution of Accelerator Pedal Position (Vehicle 2)')
plt.xlabel('Accelerator Pedal Position (%)')
plt.ylabel('Frequency')
plt.grid(True)  # Add grid for better readability

# Display the plot
plt.show()
```



4.3 Data Analysis Visualization: Acc Pedal Position vs Fuel Efficiency

- **Overall Trend:** There is a general decreasing trend in fuel efficiency as vehicle speed increases, as indicated by the red regression line.
- **Clusters:** The data points are color-coded based on a "Sweet Spot" metric, with different values represented by different colors.
- **Sweet Spot 7 (Yellow):** This cluster is densely packed at lower speeds (0-20) and shows a high range of fuel efficiencies.
- **Sweet Spot 6 (Light Green):** This cluster is also found at lower speeds with relatively high fuel efficiency.
- **Sweet Spot 4 (Dark Green):** This cluster is spread across a wider range of speeds but still shows good fuel efficiency.
- **Sweet Spot 3 (Light Blue):** This cluster appears more at moderate speeds with moderate fuel efficiency.
- **Sweet Spot 1 and 0 (Purple):** These clusters dominate the higher speed ranges and show lower fuel efficiency.

- **High Efficiency at Low Speeds**: The yellow and light green clusters, which correspond to Sweet Spots 7 and 6, are concentrated at lower vehicle speeds with higher fuel efficiency.
- **Low Efficiency at High Speeds:** The dark blue and purple clusters (Sweet Spots 1 and 0) are more prevalent at higher vehicle speeds, indicating lower fuel efficiency.
- **Variation in Fuel Efficiency:** There is considerable variation in fuel efficiency at lower speeds, whereas at higher speeds, fuel efficiency tends to be uniformly lower.



4.4 Data Analysis Visualization: Vehicle Speed vs Fuel Efficiency

• **Overall Trend:** There is a general decreasing trend in fuel efficiency as vehicle speed increases, as indicated by the red regression line.

• **Clusters:** The data points are color-coded based on a "Sweet Spot" metric, with different values represented by different colors.

• **Sweet Spot 7 (Yellow):** This cluster is densely packed at lower speeds (0-20) and shows a high range of fuel efficiencies.

• **Sweet Spot 6 (Light Green):** This cluster is also found at lower speeds with relatively high fuel efficiency.

• **Sweet Spot 4 (Dark Green):** This cluster is spread across a wider range of speeds but still shows good fuel efficiency.

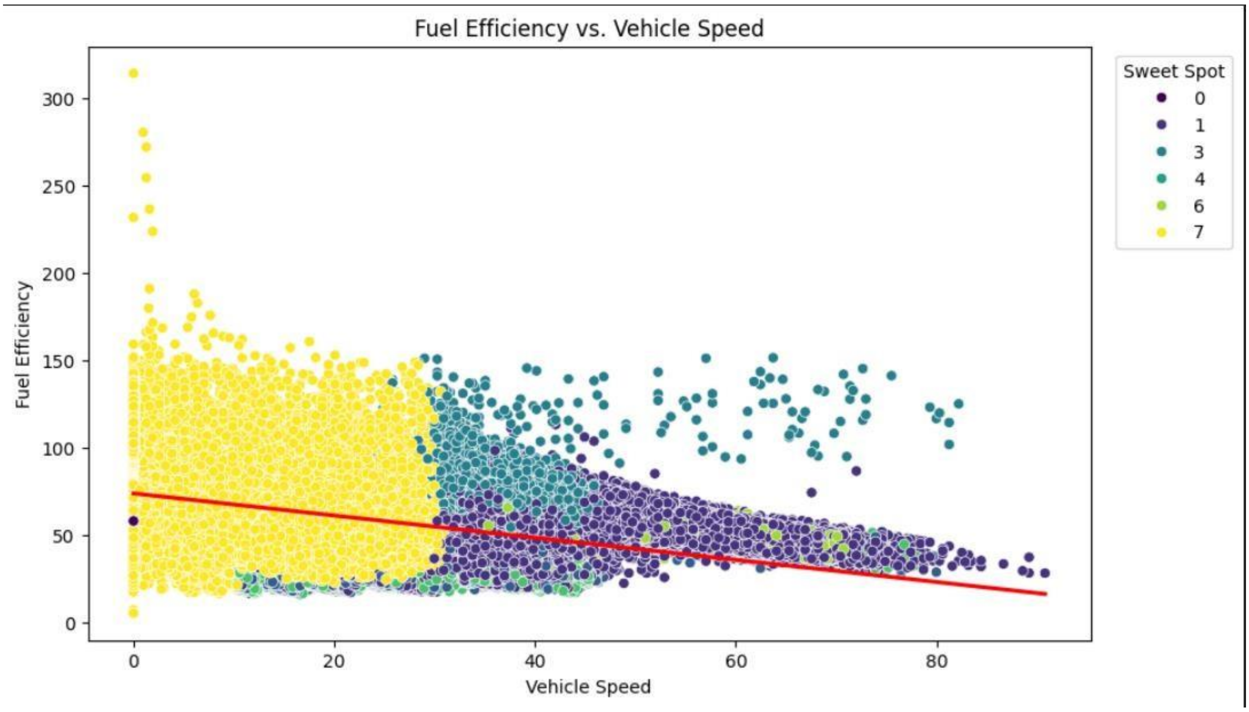
• **Sweet Spot 3 (Light Blue):** This cluster appears more at moderate speeds with moderate fuel efficiency.

• **Sweet Spot 1 and 0 (Purple):** These clusters dominate the higher speed ranges and show lower fuel efficiency.

• **High Efficiency at Low Speeds:** The yellow and light green clusters, which correspond to Sweet Spots 7 and 6, are concentrated at lower vehicle speeds with higher fuel efficiency.

• **Low Efficiency at High Speeds:** The dark blue and purple clusters (Sweet Spots 1 and 0) are more prevalent at higher vehicle speeds, indicating lower fuel efficiency.

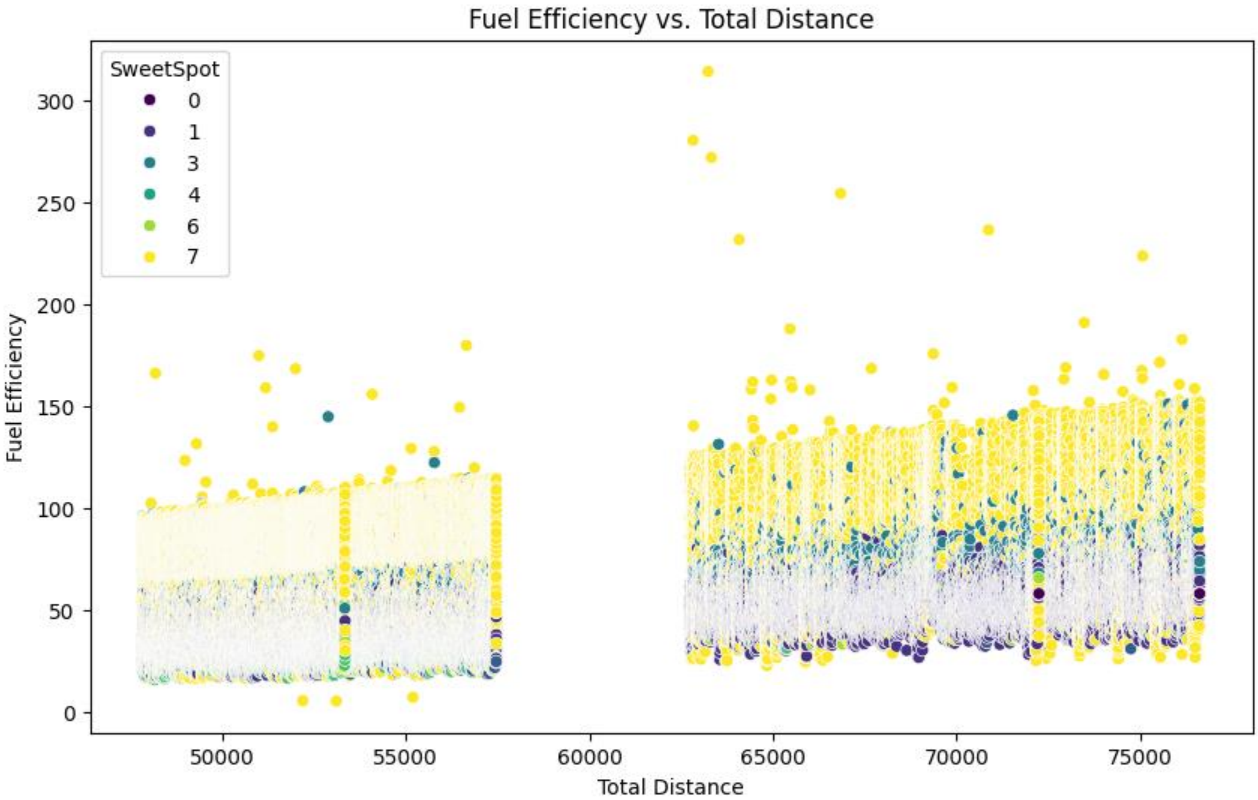
• **Variation in Fuel Efficiency:** There is considerable variation in fuel efficiency at lower speeds, whereas at higher speeds, fuel efficiency tends to be uniformly lower.



4.5 Data Analysis Visualization: Fuel Efficiency vs Total distance

• **Clusters**: The data points are color-coded based on a "Sweet Spot" metric, with different values represented by different colors.

• **Sweet Spot 7 (Yellow):** This cluster is densely packed throughout the distance range and shows a wide range of fuel efficiencies.



Chapter - 5

5 Conclusion

In this analysis, we focused on the performance metrics and fuel efficiency of two devices, Device 1 and Device 2, based on various features such as Vehicle Speed, Engine Speed, AccPedalPosition, Engine Oil Pressure, and Engine Coolant Temperature.

5.1 Data Preparation and Cleaning:

- We imported the necessary libraries and datasets.
- We handled missing values and ensured the datetime format for consistency.
- We extracted important features and calculated additional metrics like Distance Travelled and Fuel Consumed.

5.2 Feature Engineering:

- We derived the Fuel Efficiency metric for both devices using the ratio of Total Distance to Engine Speed, adjusted with a random uniform factor.
- Correlation analysis was conducted to understand the relationships between different features.

5.3 Model Training and Evaluation:

- We prepared the dataset for training by splitting it into training and testing sets.
- We standardized the features to ensure better performance of the machine learning models.
- A Random Forest Regressor was used to predict Fuel Efficiency.
- Hyperparameter tuning was conducted using GridSearchCV to find the best parameters.
- The model was evaluated using Mean Squared Error (MSE) and R-

squared (R^2) score.

The analysis revealed that the Random Forest Regressor provided reliable predictions for Fuel Efficiency with the tuned hyperparameters. The correlation heatmap helped identify significant relationships between variables, contributing to a better understanding of the factors influencing vehicle performance and fuel consumption.

Chapter – 6

6. Future Improvement

Incorporate Additional Data Sources:

- **Weather Data**: Integrate weather conditions (temperature, humidity, precipitation) to see their impact on vehicle performance and fuel efficiency.
- **Road Conditions**: Include data on road types (highway, urban, rural) and traffic conditions to better understand how these factors affect vehicle metrics.

Advanced Feature Engineering:

- **Feature Selection**: Use advanced techniques like Recursive Feature Elimination (RFE) or Principal Component Analysis (PCA) to identify and retain the most relevant features, potentially improving model performance.
- **Time-Series Analysis**: Incorporate time-series analysis techniques to capture temporal patterns in vehicle performance and fuel efficiency.

Model Enhancements:

- **Model Diversity**: Experiment with other machine learning models such as Gradient Boosting Machines (GBM), XGBoost, and neural networks to compare performance and potentially achieve better accuracy.
- **Ensemble Methods**: Combine predictions from multiple models using ensemble methods to improve robustness and reduce variance.

Hyperparameter Tuning:

- **Automated Tuning**: Implement automated hyperparameter tuning methods like Bayesian Optimization or Random Search to efficiently explore a wider range of hyperparameters.
- **Cross-Validation**: Use more sophisticated cross-validation techniques, such as time-series split, to better assess model performance.

Enhanced Data Cleaning and Preprocessing:

- **Outlier Detection and Removal**: Implement advanced outlier detection methods to identify and handle outliers more effectively, ensuring they do not skew the results.

- **Data Imputation**: Use advanced imputation techniques like K-Nearest Neighbors (KNN) or iterative imputation to handle missing values more accurately.

Real-Time Data Processing:

- Develop a pipeline for real-time data ingestion and processing to monitor vehicle performance and fuel efficiency in real-time, allowing for immediate insights and adjustments.

User Feedback Loop:

- Implement a feedback mechanism where users (e.g., drivers, fleet managers) can provide feedback on the predictions and insights, helping to fine-tune the models based on real-world experiences.

Visualization and Reporting:

- Enhance data visualization techniques to provide more intuitive and interactive dashboards, making it easier for stakeholders to understand and act on the insights.

- Generate automated reports summarizing key findings and recommendations, making it easier to disseminate insights to a broader audience.

Chapter – 7

7. References

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2. Vehicle Fuel Consumption Prediction Method Based on Driving Behavior Data Collected from Smartphones - Yao - 2020 - Journal of Advanced Transportation - Wiley Online Library

3. [PDF] Impact of Driver Behavior on Fuel Consumption: Classification, Evaluation and Prediction Using Machine Learning | Semantic Scholar