Average Fuel Consumption in Heavy Vehicles Using Machine Learning

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I. ABSTRACT

In this study, we developed customised machine learning models for fuel consumption[1] using vehicle travel distance rather than the conventional time period. Seven predictors generated from vehicle speed and road grade are combined with this method to create a highly predictive neural network model for average fuel consumption in large vehicles. To reduce fuel usage across the board, the suggested methodology can be quickly established and implemented for each individual vehicle in a fleet. The model's predictors are combined over predetermined window sizes for distance travelled. The evaluation of various window sizes reveals that a 1 km window has a 0.91 coefficient of determination and a mean absolute peak-to-peak percent accuracy in predicting fuel usage.

Keywords: Fuel consumption, machine learning, neural network, vehicle travel distance, road grade, fleet optimization, ANN, image classifier, neural network architecture

II. INTRODUCTION

Vehicle manufacturers, regulators, and consumers are all interested in FUEL consumption models. They are required during every stage of the life of the vehicle. The average fuel consumption of heavy trucks during the phase of operation and maintenance is the major topic of this article. Techniques used to create models of fuel use often fall into one of three categories: models based on physics-which come from a thorough comprehension of the physical system. These simulations explain the dynamics of the vehicle's parts. data-driven machine learning[2] models: These models represent an abstract mapping from an input space containing a chosen collection of predictors to an output space that corresponds to the desired output. Additionally, data-driven, statistical models provide a relationship between the probability.

II.A)SYSTEM ANALYSIS

In a total framework examination of a typical fuel utilization project in weighty vehicles utilizing AI, the initial step is to characterize the issue, which is to foresee the typical fuel utilization in light of different elements. Then, information assortment happens, where pertinent information, for example, authentic fuel utilization records, vehicle details, driving circumstances, climate information, and driver conduct is assembled. The gathered information is then preprocessed by dealing with missing qualities, eliminating anomalies, and normalizing or scaling highlights. Highlight choice and designing are performed to distinguish the most applicable elements that effect fuel utilization[3]. The picked calculation for demonstrating and expectation is an Artificial Neural Network (ANN). The information is parted into preparing and testing sets, and the ANN model is prepared utilizing the preparation information. The model's exhibition is assessed utilizing measurements like mean outright mistake or coefficient of assurance. Advancement methods, including hyperparameter tuning and regularization, can be applied to work on the model's presentation. When the model is viewed as good, it very well may be sent in a creation climate, where its expectations are persistently observed and assessed for exactness and unwavering quality.

II.B)EXISTING SYSTEM

Model that can be easily developed for individual heavy vehicles in a large fleet is proposed. Relying on accurate models of all of the vehicles in a fleet, a fleet manager can optimize the route planning for all of the vehicles based on each unique vehicle predicted fuel consumption thereby ensuring the route assignments are aligned to minimize overall fleet fuel consumption This approach is used in conjunction with seven predictors derived from vehicle speed and road grade to produce a highly predictive neural network[4] model for average fuel consumption in heavy vehicles. Different window sizes are evaluated and the results show that a 1 km window is able to predict fuel consumption with a 0.91 coefficient of determination and mean absolute peak-to-peak percent error less than 4% for routes that include both city and highway duty cycle segments

II.C)PROPOSED SYSTEM

Artificial Neural Network (ANN)[5] are frequently used to foster computerized models for complex frameworks. The models proposed in feature a portion of the troubles looked by AI models when the info and result have various spaces. In this review, the information is accumulated in the time area north of 10 minutes stretches and the result is fuel utilization over the distance went during a similar time span. The intricate framework is addressed by an exchange capability $F(p) = o$, where $F(\cdot)$ addresses the framework, p alludes to the information indicators and o is the reaction of the framework or the result. The ANNs utilized in this paper are Feed Forward Brain Organizations (FNN). Preparing is an iterative cycle and can be performed utilizing different methodologies including molecule swarm enhancement and back proliferation. Different methodologies will be viewed as in future work to assessment their capacity to work on the model's prescient exactness. Every cycle in the preparation chooses a couple of (input, yield) highlights from Ftr aimlessly and refreshes the loads in the organization. This is finished by ascertaining the mistake between the real result esteem and the worth anticipated by the model

II.D)FEASIBLITY STUDY

Feasibility analysis[6] begins once the goals are defined. It starts by generating broad possible solutions, which are possible to give an indication of what the new system should look like. This is where creativity and imagination are used. Analysts must think up new ways of doing things- generate new ideas. There is no need to go into the detailed system operation yet. The solution should provide enough information to make reasonable estimates about project cost and give users an indication of how the new system will fit into the organization. It is important not to exert considerable effort at this stage only to find out that the project is not worthwhile or that there is a need significantly change the original goal. Feasibility of a new system means ensuring that the new system, which we are going to implement, is efficient and affordable. There are various types of feasibility to be determined. They are,

II.D.1)Economically Feasibility

As a portion of this, the expenses and profits related with the implemented systems are to be associated. The project is carefully feasible only if tangible and intangible assistances balance the cost. We can say the implemented system is feasible founded on the following grounds

II.D.2)Technical feasibility

In the technical feasibility study, one has to assess whether the implemented system can be established using existing technology or not. It is intended to implement the implemented system in JSP. The project enabled is theoretically feasible since the following reasons.

1. Recognise the various technologies incorporated within the proposed system: We must be extremely clear on the technologies that will be needed for the creation of the new system before we start the project.
2. Determine if the organisation presently has the necessary technologies: Is the organisation equipped with the necessary technology? In such case, is the capacity adequate? For instance, "Will the new reports and forms needed for the new system be compatible with the present printer?

II.D.3)Operational Feasibility

This project is operationally feasible[15] for there is necessary support from the project organization and the users of the implemented system Implemented system absolutely does not damage and determination not create the corrupt results and no problem will ascend after Search document implementation[7] of the system.

1.User-friendly: Customer will use the forms for their various transactions i.e.. for adding new routes, viewing the routes details. Also, the Customer wants the reports to view the various transactions based on the constraints. These forms and reports are generated as user-friendly to the Client.

2.Reliability: The package wills pick-up current transactions on line. Regarding the old transactions, User will enter them in to the system.

3.Security: The web server and database server should be protected from hacking, virus etc.

III.SPECIFICATION

III.A)HARDWARE REQUIREMENTS (Minimum Requirement)

1.RAM:4GB+RAM
2.PROCESSOR: i3 10th Gen 2.2 Ghz

III.B)SOFTWARE REQUIREMENTS

1.Domain: Python
2.Version: Python IDLE (3.11.2)

3.Code Editors: PyCharm
4.Frameworks and Dependencies: tkinter,matplotlib,Keras,numpy,pandas
5.Operating System: Windows 10

IV.CODE EDITORS

IV.A)PyCharm

PyCharm is an integrated development environment[8] (IDE) used In computer programming, specifically for the Python language. It is developed by the Czech company Jet Brains (formerly known as IntelliJ). It provides code analysis, a graphical debugger, an integrated unit tester, integration with version control systems (VCSes), and

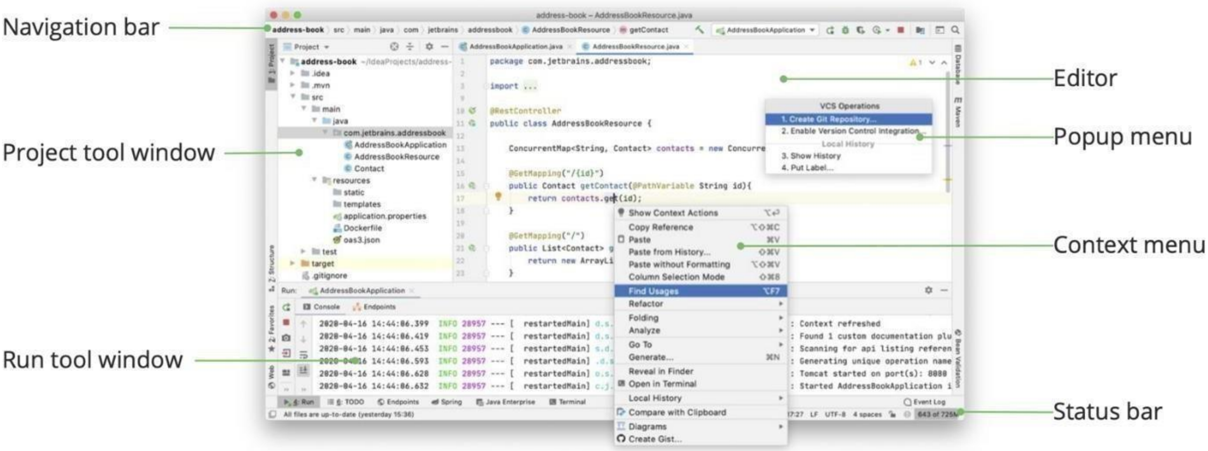

Figure1: PyCharm screen

supports web development with Django as well as data science with Anaconda
•Coding assistance and analysis, with code completion, syntax and error highlighting, linter integration, and quick fixes
•Project and code navigation: specialized project views, file structure views and quick jumping between files, classes, methods and usages
•Python refactoring: includes rename, extract method, introduce variable, introduce constant, pull up, push down and others
•Integrated Python debugger
•Integrated unit testing, with line-by-line code coverage
•Google App Engine Python development
•Version control integration: unified user interface for Mercurial, Git, Subversion, Perforce and CVS with change lists and merge
•Support for scientific tools like matplotlib, numpy and scipy [professional edition only]
PyCharm provide an API so that developers can write their own plugins to extend PyCharm features. Several plugins from other JetBrains IDE also work with PyCharm. There are more than 1000 plugins which are compatible with PyCharm

IV.B)DEVELOPMENT TOOLS AND TECHNOLOGIES:

IV.B.1)PYTHON:

Python is an interpreter, interactive, object-oriented programming language. It incorporates modules, exceptions, dynamic typing, very high-level dynamic data types, and classes. Python combines remarkable power with very clear syntax. It has interfaces to many system calls and libraries, as well as to various window systems, and is extensible in C or C++.

IV.B.2)Python is portable

it runs on many Unix variants, on the Mac, and on Windows 2000 and later. When he began implementing Python, Guido van Rossum was also reading the published scripts from “Monty Python’s Flying Circus”, a BBC comedy series from the 1970s. Van Rossum thought he needed a name that was short, unique, and slightly mysterious, so he decided to call the language Python.

Python is one of those rare languages which can claim to be both simple and powerful. You will find yourself pleasantly surprised to see how easy it is to concentrate on the solution to the problem rather than the syntax and structure of the language you are programming in. Python is simple and minimalistic language. Reading a good Python program feels almost like reading English, although very strict English! This pseudo- code nature of Python is one of its greatest strengths. It allows you to concentrate on the solution to the problem rather than the language itself. Due to its open-source nature, Python has been ported to (i.e., changed to make it work on) many platforms. All your Python programs can work on any of these platforms without requiring any changes at all if you are careful enough to avoid any system-dependent features.

V.RELATED WORK

V.A)Machine learning for fuel consumption prediction in fleet cars Comparative analysis

A vehicle's fuel consumption is influenced by both internal variables like distance, load, vehicle attributes, and driver behaviour, as well as external elements like weather, traffic, and road conditions. It's possible that not all of these variables can be monitored or are accessible for the fuel usage study. When just a portion of the aforementioned characteristics are accessible as a multivariate time series from a long-distance public bus, this is the situation we are going to be looking at. Since only accessible data can be used to estimate and/or anticipate fuel usage, the issue is to capture as much of the indirect effects of other internal and external elements as possible. Improving vehicle fuel economy and combating fraud in fleet management[9] require the ability to model and anticipate fuel usage. As a result, the difficulty is to model and/or estimate fuel usage using only the data that is now accessible while also inadvertently accounting for as many impacts from both internal and external sources. Machine learning (ML) is appropriate in this study since the model may be created by discovering patterns in the data. In this study, given all the relevant parameters as a time series, we assess the prediction performance of three ML approaches in estimating the fuel consumption of the bus.

V.B)fuel consumption modelling for heavy and medium-duty vehicles based on driving cycle characteristics

Data gathered from chassis testing on a parcel delivery diesel truck operating over the Heavy Heavy-Duty Diesel Truck (HHDDT)[10], City Suburban Heavy Vehicle Cycle (CSHVC), New York Composite Cycle (NYCC), and hydraulic hybrid vehicle (HHV) drive cycles were used to develop and verify a polynomial model, a black box artificial neural net model, a polynomial neural network model, and a multivariate adaptive regression splines (MARS) model. Because HHDDT incorporates a range of drive parameters, including high speed, acceleration, idling, and deceleration, it produced the greatest predicted results. MARS provided the greatest prediction performance of the four model methods, with an average percent error of 1.84% throughout the four chassis dynamometer driving cycles. The methods were used on actual data in order to assess the prediction models' accuracy further. The average percent error for MARS across four actual road segments was 2.2%, outperforming the other three techniques.

V.C)European experimental monitoring of co2 emissions from HDV demonstration of the proposed methodological strategy

In contrast to passenger cars and light commercial vehicles[11], which are monitored using chassis dyno measurements, it was determined that the core of the proposed methodology should be based on a combination of component testing and vehicle simulation. This is because the HDV market is diverse and has unique characteristics. Realistic fuel consumption results and precise simulation of the operation of various vehicle components are prioritised. A new legal framework for tracking and disclosing CO2 emissions[12] from Heavy Duty Vehicles (HDVs) in Europe is being developed by the European Commission in collaboration with Heavy Duty Vehicle manufacturers, the Graz University of Technology, and other consulting and research organisations. A number of tests were performed on 2 distinct trucks: a DAF 18 tonne Euro V rigid truck and a Daimler 40 tonne Euro VI long haul delivery truck with semi-trailer. Both on-road and in the HDV chassis dyno laboratories of the Joint Research Centre, measurements were made. The measurements' results were used to validate a car simulator (car Energy Consumption Calculation Tool, or VECTO), which was created to be utilised for official monitoring reasons.

VI.MODULE DESCRIPTION

There are five modules in this project.

Upload Heavy Vehicles Fuel Dataset : Using this module, we can upload train dataset to application. Dataset contains comma separated values.

Read Dataset & Generate Model: Using this module, we will parse comma separated dataset and then generate train and test model for ANN from that dataset values. Dataset will be divided into 80% and 20% format, 80% will be used to train ANN model and 20% will be used to test ANN model.

Run ANN Algorithm: Using this module, we can create ANN object and then feed train and test data to build ANN model.
Predict Average Fuel Consumption: Using this module, we will upload new test data and then ANN will apply train model on that test data to predict average fuel consumption for that test records.
Fuel Consumption Graph: Using this module, we will plot fuel consumption graph for each test record. In above test data class value as fuel consumption is not there and when we applied this test record on ANN model then ANN will predict fuel consumption class value for that test record. Entire train and test data available inside 'dataset' folder

VII.DATACOLLECTION AND SUMMARIZATION

A single vehicle with an estimated mass of 8,700kg that was exposed to a variety of drifters, including motorway and urban traffic in the Indianapolis area, was used to collect obligation cycles for the model. The SAE J1939 standard for sequential control and correspondences in rock solid vehicle organisations[13] was used to gather information. Twelve drivers were asked to demonstrate either good or bad behaviour throughout two different courses. Drivers who behaved properly were supposed to slow down and, when it was safe to do so, let the car drift. The distribution of drivers and courses across the informative collection isn't consistent since some drivers participated more than others. The vehicle's CAN transport generated 3, 302, 890 interesting data points for this field test, which had an overall distance of 778.89 km and 56 excursions with varying distances. The majority of the journey was between 10 and 15 km long. Engineered obligation cycles spanning a long distance were obtained by gathering bits from the randomly selected field obligation cycles in order to increase the quantity of data of interest.

VII.A)Model Predictors:

The model's indications needed to be produced through a few handling phases. Street level and gearbox yield speed[14] are two estimations from which these indications are obtained. The initial handling stage included a street level inspection and determining the vehicle speed from the yield speed of the gearbox. An on-board inclinometer was used to measure street level, and it was down-inspected to 1 Hz. A review of the data also revealed a clear correlation between the vehicle speed and the gearbox yield speed indicated by the accompanying condition:

$$\text{Vehicle Speed} \approx 59.3 \times \text{Transmission Result Speed}$$

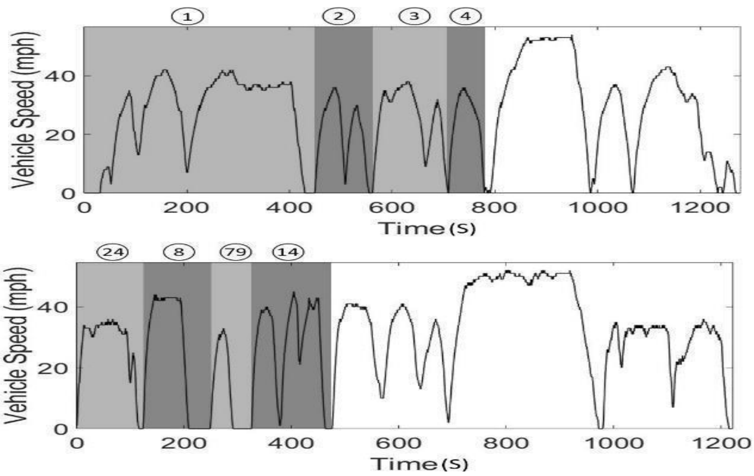

Figure2.The first four segments of a sample real duty cycle (top). A sample synthetic duty cycle created by concatenating segments 24, 8, 79, and 14 from the real data (bottom)

TABLE I

NUMBER OF DATA POINTS (I.E., WINDOWS) AND TOTAL DISTANCE FOR THE TRAINING (F(x)tr) AND THE TESTING (F(x)ts) DATA SETS WITH VARYING SIZE WINDOWS (I.E., 1, 2, AND 5 km.)

Window size	F(x)tr		F(x)ts	
	Number of Points	Distance (km)	Number of Points	Distance (km)
x = 1 km	20,000	20,000	32,089	32,089
x = 2 km	20,000	40,000	23,106	46,212
x = 5 km	20,000	100,000	6,061	30,305

The top predictors were chosen because it is considered that they accurately reflect vehicle dynamics, driver behaviour, and the route's effect on the model's intended output (i.e., fuel consumption). Particularly, a prior study claims that mechanical speed and characteristic acceleration are highly predictive of the fuel consumption for a specific duty cycle. This study contends that the inertia works necessary to accelerate the vehicle is closely related to characteristic acceleration[16], and the mechanics speed square accurately depicts the effect of aeromechanics on fuel consumption.

VII.B)MODEL OUTPUT

The average amount of gasoline consumed over all of the journeys varies, according to a study of the segments in the real data gathered from the field. For instance, throughout the course of whole excursions, a 20% difference in fuel use was found between excellent and bad driving behaviour. Additionally, differences in typical fuel usage are seen for various window widths. The model's output is the average fuel consumption in litres per 100 km for each window. Fuel prices are taken from the will bus in order to calculate the average use. Discontinuities in the fuel rate are found from one phase to the next because false duty cycles are formed from a random selection of genuine duty cycle segments[17], as in the case of road grade. Because gasoline prices are averaged throughout the whole window to determine the output of the model (i.e., average fuel usage), the effects of these discontinuities are not significant. In conclusion, the proposed model's input characteristics are all obtained using the aforementioned methods from the vehicle speed and the road grade samples taken at a rate of 1 Hz. A telematics device can provide these variables.

TABLE II

PREDICTIVE ACCURACY OF THE FUEL CONSUMPTION MODELS FOR 1, 2 AND 5 km AGGREGATION WINDOWS.

Window	1 km	2 km	**5 km**
CD	0.91 (0.0066)	0.87 (0.0085)	0.79 (0.0136)
RMSE (l/100km)	0.0132 (0.0005)	0.0142 (0.0005)	0.0234 (0.0008)
MAE (l/100km)	1.88 (0.0626)	1.69 (0.0515)	1.43 (0.0466)
MAPEpk	3.74% (0.12%)	4.20% (0.13%)	5.83% (0.19%)
Points	32,089	23,106	6,061

Table II demonstrates that, for all measures, the 1 km model outperforms the other two window widths. These performance measures assess the model's performance point-by-point, as was already described. In particular, the 1 km model's coefficient of determination (CD)[19] is equal to 0.91, demonstrating that the model can monitor real fuel use for each 1 km of travel. The CD gets smaller as the window gets bigger. High precision fuel sensors are used, yet the suggested model still outperforms them in terms of MAE and CD. The models' RMSE is likewise smaller than 0.025 l/100 km, which is better than the outcomes. Nevertheless, this paper's test distance is greater. The performance measures shown in Table II appear to illustrate that the proposed models use highly predictive input characteristics that are appropriately transferred to the model's output space. The AIW values of the predictors are calculated and compiled in Table III to help understand the impact of each one.

VII.C)MODEL VALIDATION

The neural network model receives its input from the seven predictors that are given in Section IV. The network's bottom layer is made up of this. Next, a hidden layer with 5 neurons receives input from the first layer. The hidden layer then transmits information to an output player made up of only one neuron. Figure 3 displays the RMSE over the course of training for three models with 1, 2, and 5 km window widths. Each data point in the top panel corresponds to the RMSE[18] values after the model was trained using a set of 500 windows. According to this graphic, all models converge to an RMSE value of less than 0.2 l/100 km. The convergence rates for the models vary, though. In actuality, the 5 km's RMSE value drops to 0.08 l/100km as the model converges from its initial value of 0.16 l/100km after 500 training windows. For the 1 km model, the comparable values are 0.34 and 0.14 litres per 100 km, respectively.

TABLE III

ADJUSTED INFLUENCE OF WEIGHTS (AIW) FOR THE PREDICTORS IN THE PROPOSEDMODEL

Window	1 *km*	2 *km*	5 *km*
No. of Stops	1.49	2.29	4.63
Stop Time	0.62	1.24	3.44
Avg. Moving	13.73	10.78	8.98
Speed *a* ˜ *v*2 *aero*	12.47	14.32	12.98
CKE CPE	11.73	11.64	10.30
Bias	17.04	16.13	12.26
	13.73	11.45	9.38
	29.21	32.15	38.03

As the window size rises, the number of stops and the stop duration become more crucial. This is predicted given that there are less stops visible in the 1 km view than in the 2 or 5 km windows. Across all window sizes, the remaining predictors all show strong AIW. In actuality, models with any of these indicators removed had reduced prediction accuracy. Additionally, Table III shows that the two novel predictors included in this study had an equivalent impact on predicting fuel consumption to average moving speed, characteristic acceleration, and aerodynamic speed.

VIII.SYSTEM IMPLEMENTATION

Data collection and preprocessing, feature selection and engineering, model selection and training, model evaluation, model optimisation, deployment, and ongoing monitoring and maintenance comprise the overall machine learning implementation of the average fuel consumption project for heavy vehicles.

1. Data Gathering and Preprocessing: Gathering pertinent data and putting it together by dealing with outliers, missing numbers, and normalisation.
2. Feature Selection/Engineering: Choosing or developing the key elements that have the most influence on fuel consumption.
3. Model Selection and Training: Using the data that has been gathered and processed, selecting a suitable machine learning model, such as an Artificial Neural Network (ANN), and training it.
4. Model assessment: Using the right assessment metrics and testing data, determine how well the trained model performed.
5. Model Optimisation: Using methods like hyperparameter tuning[20], regularisation, or sophisticated model architectures, the model is fine-tuned.
6. Deployment: Including the improved model in a system or production environment to estimate actual fuel use.
7. Monitoring and Maintenance: Constantly keeping an eye on the performance of the deployed model, spotting concept drift, and to provide precise and trustworthy predictions, the model may need to be updated or retrained.

VIII.A)PURPOSE

The goal of the average fuel consumption project for heavy vehicles using machine learning is to create a predictive model that precisely predicts the fuel consumption of heavy vehicles based on different variables like vehicle specifications, driving circumstances[21], weather data, and driver behaviour. The project seeks to give insights and tools that can assist optimise fuel economy[23], save operating costs, and make wise decisions regarding fuel usage in heavy truck operations by utilising machine learning techniques.

VIII.B)SYSTEM MAINTENANCE

Several crucial tasks are involved in system maintenance for the project employing machine learning to estimate average fuel usage in heavy vehicles:

1. Data gathering: Compile pertinent information, such as past fuel consumption statistics, vehicle specs, road conditions, weather information, and driver behaviour.
2. Data preprocessing: To guarantee data quality and consistency, tidy the obtained data by managing missing values, eliminating outliers, and normalising or scaling features.
3. Data Updates: To include new information and preserve data accuracy, the model's data, such as fuel consumption records and other pertinent data sources, should be updated on a regular basis.

4. Feature Selection/Engineering: From the preprocessed data, choose or engineer the elements that have the greatest influence on fuel usage, taking into account things like vehicle specs, road conditions, weather information, and driver behaviour.
5. Data Monitoring: Continually check the accuracy and integrity of the data to make sure the input data is trustworthy and up-to-date. to maintain precise forecasts of fuel usage.
6. Data Drift Detection: Keep an eye out for changes in the underlying data distribution over time, also known as idea drift. Implement strategies for detecting and controlling drift, such as keeping an eye on feature distributions and assessing the effects they have on forecasts of fuel use.
7. Data Storage and Accessibility: Ensure that the data is safely kept and made available to the machine learning system in order to provide effective training, assessment, and future upgrades.
The system can produce accurate and trustworthy projections[22] of the typical fuel consumption of heavy trucks by efficiently handling the data throughout the project lifetime, from collection and preprocessing through updates and monitoring.

IX.CONCLUSION

machine learning model that may be created to be beneficial for each heavy vehicle in an armada. The seven indications that make up the model are: the number of stops, the stop duration, the average moving rate, the growth in trademark speed, the squared streamlined speed, the change in active energy, and the change in potential energy[24]. The final two signs are discussed in this essay to help readers identify the normal and distinctive ways that each vehicle behaves. All of the model's indications are derived from street level and vehicle speed. Telematics devices, which are fast becoming an essential component of linked automobiles, may quickly access these parameters. Additionally, these two elements make it easy to figure out the signs.

IX.A)SCOPE FOR FUTURE DEVELOPMENT

The average fuel consumption project for heavy trucks utilising machine learning has the potential to lead to a number of developments in the future. These include investigating more sophisticated prediction models, such as ensemble approaches or deep learning architectures, to improve the precision and dependability of forecasts[25] of fuel use. Sensors and telematics data may be used to provide real-time monitoring, providing quick feedback and fuel efficiency analyses. To proactively detect maintenance needs and optimise fuel use, predictive maintenance capabilities can be implemented. The project's scope can also be expanded by incorporating advanced analytics techniques, predictive analytics for maintenance and fuel cost estimation, environmental impact analysis, and optimal route planning algorithms that take fuel consumption into account. These are the areas where the project focuses. may help heavy vehicle operations become more cost-effective, more environmentally friendly, and capable of making well-informed decisions.

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Ijji Saikiran studying her 2nd year, Master of Computer Applications in Sanketika Vidya Parishad Engineering College, affiliated to Andhra University, accredited by NAAC.With her interest in machine learning method and as a part of academic project,he used Average Fuel Consumption in Heavy Vehicles using machine learning algorithm by the Artificia Neural Network. As a result of a desire to comprehend the flaws in conventional reporting and to preserve timely and high-quality report output in Fuel Consumption Graph. A completely developed project along with code has been submitted for Andhra University as an Academic Project. In completion of her MCA.