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Average Fuel Consumption for Heavy Vehicles Using Machine Learning Techniques

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ABSTRACT

As can be observed, the price of crude oil has been continuously rising over the last several years despite the fact that some countries are experiencing a lack of fossil resource supplies. The implementation of this program is being carried out so that in the future we will be able to triumph over the challenge. This research suggests using a data summarizing strategy that is focused on distance rather than the more conventional time periods when it comes to the process of constructing individual machine learning models for fuel consumption. This research was carried out by the authors of the aforementioned study. When paired with seven predictors that were obtained from the speed of the vehicle and the slope of the road, this method created a model that was not only highly predictive but also fairly efficient. The approach that was presented may be easily established and put into practice for each individual vehicle in a fleet in order to enhance fuel economy across the board for the whole fleet.

KEY WORDS: Vehicle modeling, neural networks, average fuel consumption, data summarization, fleet management.

1.INTRODUCTION:

It is essential for manufacturers, regulators, and customers to have precise models of the amount of gasoline used by their vehicles. In order to be deemed essential, it is required that they remain present for the whole of the vehicle's life cycle. Simulating the normal quantity of gasoline that large cars use is the primary focus of our attention throughout the whole of the portion of our research that is devoted to operation and maintenance. Models grounded on physics, each of which is generated from a comprehensive knowledge of the underlying physical system, are not going to be used in the construction of the models that will be used to estimate fuel consumption. This is the most general statement regarding the methods that will not be used to construct models for this purpose. These models describe the dynamics of the vehicle's components at each stage of the operation by using exact mathematical equations. models that are informed by data and are constructed via machine learning. And express an abstract mapping between a house that consists of a specific set of predictors and a house that represents the target output, which in this case is the average fuel consumption. The goal output is the amount of gasoline that is used on average. The homes are, in order, the input houses, the output houses, and the ones in between. Statistical models are used. These models are likewise data-driven, and they provide a mapping between the probability distribution of a certain collection of predictors and also the outcome that is wanted. The relevance, utility, and validity of each of the aforementioned techniques in relation to the needs of the application at hand are the key points of disagreement amongst them all. The paper is structured in the following manner: In Section II, a literature overview of the prior work done on diabetes prediction is presented, as well as a classification system for machine learning algorithms. The rationale for working on this issue is presented in Section III. In Section IV, a potential model for diabetes prediction is presented and addressed. The findings of the experiment are presented in Section V, which is then followed by a Conclusion and References.

2. LITERATURE SURVEY

Average fuel usage has been modeled using physics-based, machine learning, and statistical models. The Environmental Protection Agency and the European Commission created entire vehicle simulation models grounded on physics [1, 2]. When compared to actual flowmeter results, these models can forecast average fuel consumption within a margin of error of 3%[2]. On the opposite end of the modeling spectrum are statistical processes that are implemented under tight testing settings to assure that the reported findings are standardized and reproducible, but at the expense of a large development effort. Using well-defined statistical methodologies for duty cycles derived from segments of actual journeys, the model suggested by the Code of Federal Regulation (CFR) [5] may predict fuel consumption for new cars. Similarly, trucks and buses may utilize the SAE J1321 [6] standard to calculate their expected fuel consumption after aftermarket upgrades or in different operating situations. This benchmark uses actual field data obtained under comparable operating circumstances to evaluate cars that are otherwise identical. In [13], for instance, the standard was used to evaluate the effects of engine, gearbox, and axle lubricant changes on the fuel economy of a control car and two test vehicles. In [8], three fuel technologies were evaluated in two vehicles utilized in coal mines using this same criterion.

Several studies have shown that machine learning models are superior to other methodologies for predicting fuel consumption because of their flexibility and ability to apply to a wide range of vehicles and operating circumstances. In the following sections, we will examine these models in detail, focusing on their underlying machine learning approach, input space representation, and output space representation, respectively.

To model gas use, several machine learning methods have been applied and compared. Some examples of such comparisons are [3] which compares gradiant boosting to neural networks and random forest, [4] which compares neural networks to multivariate regression splines, and [7] which compares support vector machines to neural networks and random forest. These researches choose a preferred method based on their findings. Yet, as noted in [7] and [14], the similarities between these strategies outweigh the differences. We attribute the variations mainly to diverse approaches to information amassment and synthesis. As neural networks are particularly well-suited for modeling purposes, we decided to employ them in this article.

There is a wide range of uncertainty in the input of the many fuel consumption models that have been developed. A more comprehensive model might try to account for factors including driver behavior, vehicle dynamics, and environmental effects.

3.PROPOSED SYSTEM

To accurately estimate the average fuel consumption of large trucks, this research aims to build a well-defined average fuel consumption utilizing ANN Algorithms. MySQL databases keep track of the vehicle count and provide timestamps so that the data may be verified at any moment. The desktop program that goes along with this will make use of the predicted automobiles. The desktop program will also provide tools like car data visualization based on various variables. In order to cut down on gasoline costs, the primary goal of this technique is to identify heavy vehicles' typical fuel consumption rates. All the key fuel issues of today were also uncovered by this experiment. The initiative will alleviate the present issue of high gasoline prices.

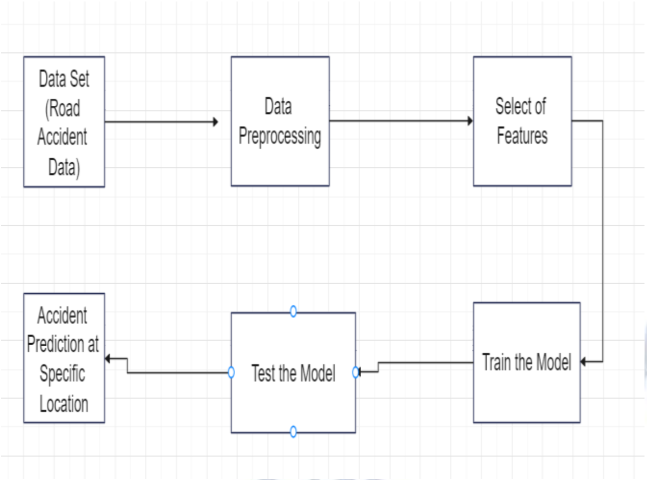

Figure 1: Block Diagram for Proposed System

4. RESULTS

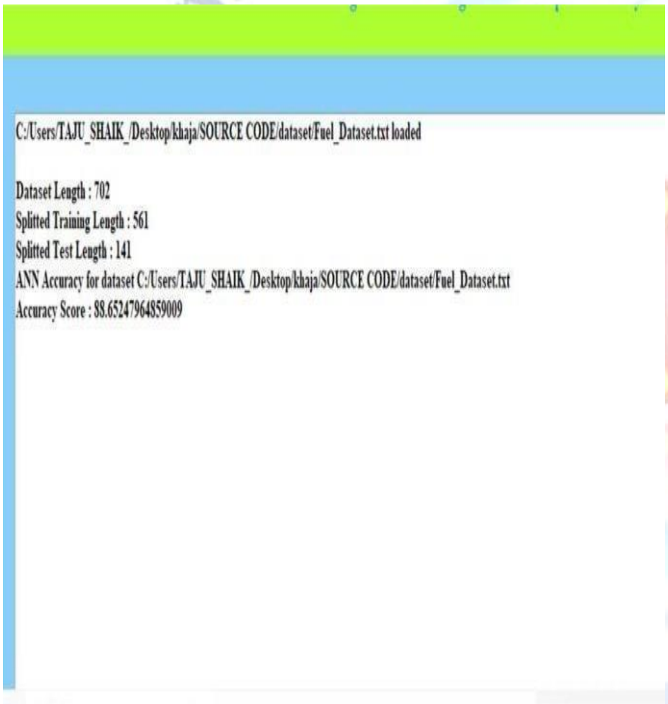

Figure 2: Results of the proposed algorithm

5. CONCLUSION

Our goal with this project was to create a machine learning-based strategy for estimating fuel consumption in heavy-load cars and improving fuel efficiency. Number of stops, time spent stopped, average speed, characteristic acceleration, aerodynamic speed square, kinetic energy change, and potential energy change are the seven predictors used in the model. Vehicle speed and road gradient are the only inputs used to generate the model's predictions. We educated the algorithm using data from several sources. For better accuracy predictions and graph plotting, we divide the data into training and testing sets during training. Based on our analysis, we expect the algorithm to significantly cut down on gasoline use.

In addition, future research should analyze how frequently a model must be synced with the physical system through online training to preserve the accuracy of its predictions and determine the minimum distance necessary for training each model.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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