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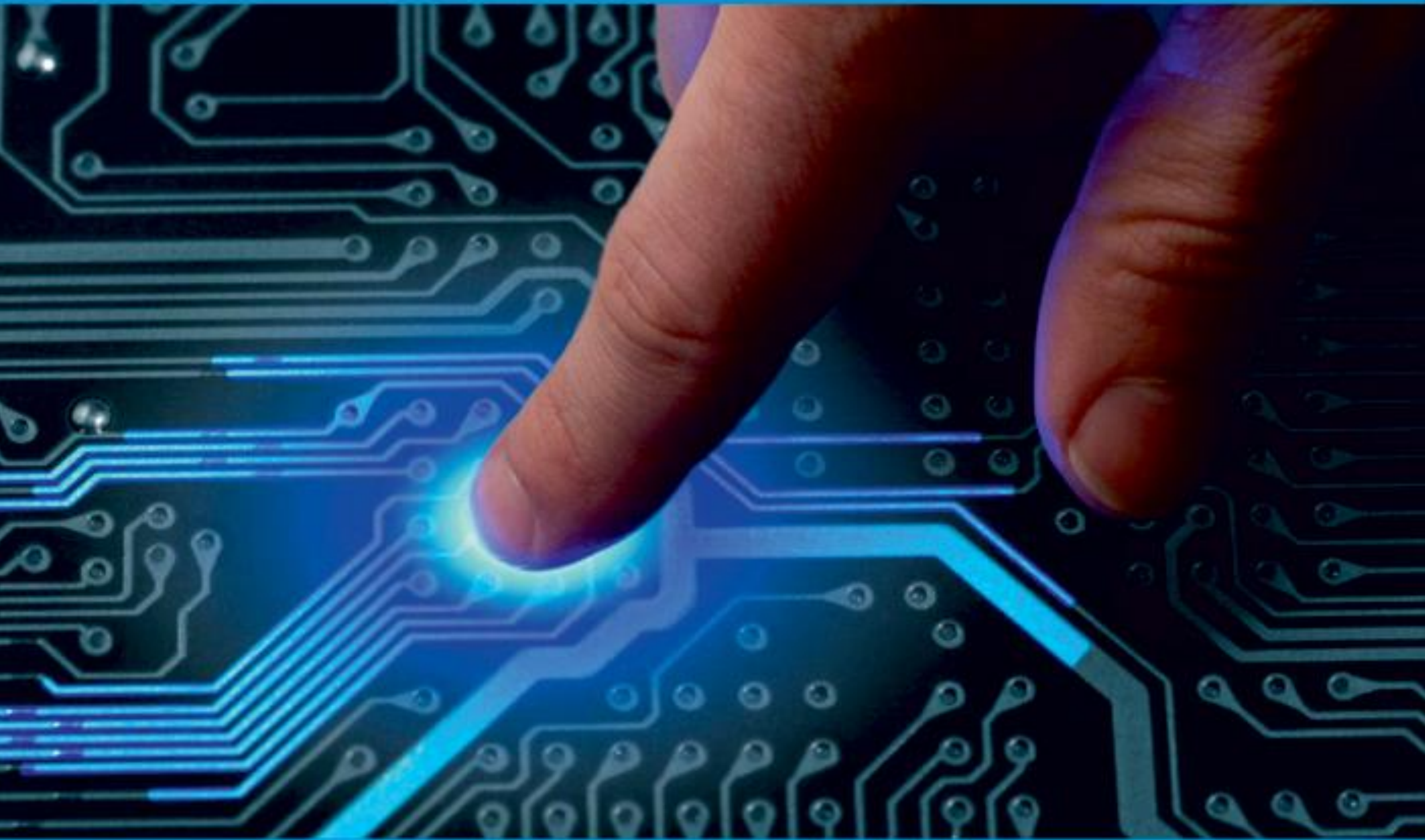

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Fuel Efficiency Prediction Using Machine Learning

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ABSTRACT: In this paper enhancing the accuracy of the fuel consumption prediction model with Machine Learning to minimize Fuel Consumption. This will lead to an economic improvement for the business and satisfy the domain needs. We propose a machine learning model to predict vehicle fuel consumption. The proposed model is based on the Support Vector Machine algorithm. The Fuel Consumption estimation is given as a function of Mass Air Flow, Vehicle Speed, Revolutions Per Minute, and Throttle Position Sensor features. The proposed model is applied and tested on a vehicle's On-Board Diagnostics Dataset. The observations were conducted on 18 features. Results achieved a higher accuracy with an R-Squared metric value of0.97than other related work using the same Support Vector Machine regression algorithm. We concluded that the Support Vector Machine has a great effect when used for fuel consumption prediction purposes. Our model can compete with other Machine Learning algorithms for the same purpose which will help manufacturers find more choices for successful Fuel Consumption Prediction models.

KEYWORDS: Machine Learning; Ship Fuel Consumption Prediction; Black-Box Model; White-Box Model; Convolutional Neural Networks

I. INTRODUCTION

1. OVERVIEW OF THE PROJECT

The international shipping community is paying more attention to the issue of green house gas (GHG) emissions with the gradual warming of the global climate. Accordingto the Fourth International Maritime Organization (IMO) GHG Study, the carbon intensity (i.e., CO_2 emissions per unit of Gross Domestic Product) of international shipping decreased by 10.7% between 2012 and 2018, while annual GHG emissions rose by 9.6%. In general, the international shipping industry accounts for approximately2% of global anthropogenic GHG emissions.

1.1 OBJECTIVES OF THE PROJECT

The objectives of the project are as stated below:

1. To develop a system to provide a more effective way of short-listing
2. To determine the key skill characteristic by defining each expert's preferences and ranking
3. To automate the process of requirement specifications and applicant's
4. To conduct online aptitude and personality
5. To produce ranking decisions that would have relatively higher consistency than those of human

II. SYSTEM ANALYSIS

1. EXPERIMENT DESIGN

It suggests that driving behavior is affected by various factors such as street design, traffic management methods, traffic conditions, weather conditions and the driver's mental andphysicalcondition. In order to evaluate the effect of the driver's condition on vehicle fuel consumption and simplify the verification process, in this study we fixed the vehicle type, trip route and weather conditions used in our experiment. The only variable factors are the drivers (i.e., their driving behavior) and the traffic conditions. Ifmorethan oneroutewereusedinthe experiment, it would be difficult to determine which factors were primarily responsible for variation in fuel consumption. Therefore, all of the data for our experiment was collected using a fixed route which included some variation in road types. Examples of the two typesof

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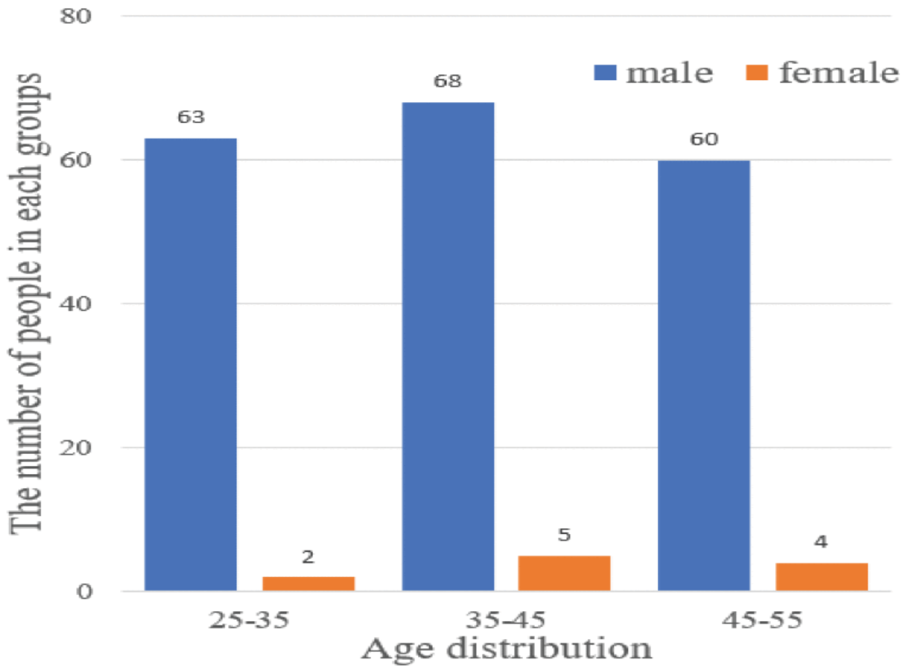
roads used in our study are shown in Fig. 2. The total distance of all of the road segments was about 15.2 km, which consisted of a 5.3 km expressway loop with two lanes in each direction and 9.9 km of ordinary road with one lane in each direction.

2. DATA COLLECTION AND REDUNDANT DATA PRUNING

The data collection system (DCS) in Fig. 5is divided into three parts: a vehicle- mounted data collection system (VMDCS), a wireless transmission system (WTS) and a data center (DC). The VMDCS uses On-Board Diagnostics (OBD) to obtain the vehicle's operating information from the ECU, and uses GPS to track the vehicle's position. The WTS uses a wireless transmission unit (WTU) installed on the vehicle which communicates with the base station via 4G broadband to upload the collected data. Messages from the WTS include a receiving module IP address so that the data can be transmitted to the DC via the internet. The DC server shows the vehicle's position and real-time vehicle information on the Web. The collected data is stored in an SQL database.

In order to improve calculation efficiency, we selected vehicle operation data with a strong relationship to driving behavior, and used the Pearson correlation coefficient (PCC)[37] to determine the relevance of each parameter to vehicle fuel consumption. We treated positive and negative acceleration as different parameters because their effects on fuel economy differ. For example, when calculating fuel cost, if negative acceleration is less than zero, instantaneous fuel consumption is zero. The calculated correlation coefficients for various features are listed inFig. 6, where PCC value$\rho$is represented by different color bars according to the following standard guidelines; when$|\rho|>0.5$=strong correlation, when$0.5>|\rho|>0.3$=moderate correlation, when $|\rho|<0.3$=weak correlation[38].InFig.6, 'Negative acc' and 'Negative acc variance' have a negative correlation with fuel consumption, so in fact, the PCC of these two parameters are negative values. Then, before using an unsupervised clustering method to abstract the data distribution features, we first pruned the weakly correlated data parameters.



III. FUEL CONSUMPTION CALCULATIONT

Consumption, we integrated instant fuel consumption information from the ECU to obtain accumulated fuel consumption data. In order to verify the results of ourcalculations, we compared our calculated results with the results from afuel consumption analyzer under various traffic conditions. The differences between these two fuel consumption measurement approaches are shown in Table 1.

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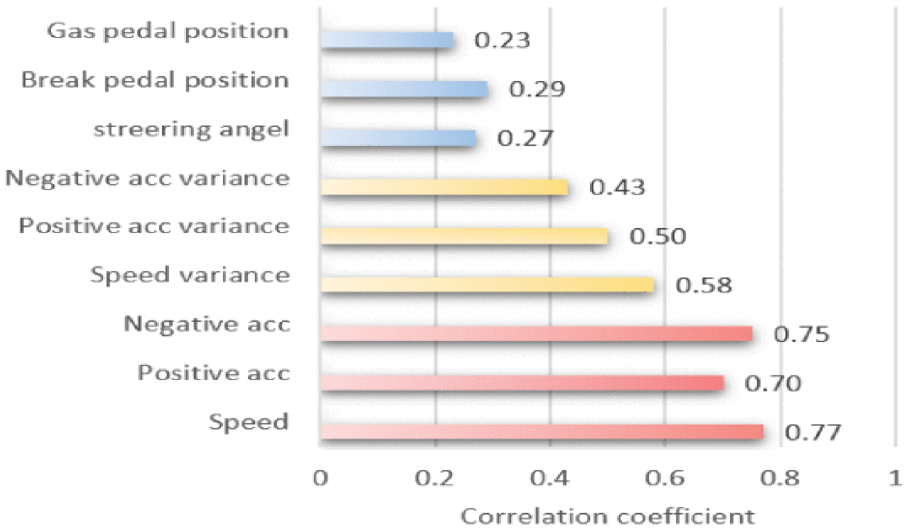
Road type / Vehicle load	Urban road	Expressway	Rural road
No-load	4.85%	1.28%	2.18%
Full-load	5.94%	0.81%	3.65%

From the data in Table 1, we can conclude that the difference between our calculation method and actual fuel consumption is less than 6%. As the route used in our experiment is only15 km in length and the goal of the Study is to evaluate the effect of driving behavior on fuel consumption, this difference can be ignored.

3. DATA SEGMENT CONSTRUCTION

As our research goal is to analyze and predict the impact of driving behavior on fuel consumption within a limited time frame (25 to 35 minutes), in this section we describe the spectral clustering method we used to compare inner similarity within the data set, so as to cluster data with similar features into the same cluster. Our spectral clustering method can only handle data sets of the same size. The data collection rate was 10Hz and we collected 15,000-21,000 data points per circuit of the driving route (we treated each circuit of the driving route as an independent data set). Since the amount of data collected in each data set varied, we needed to compress each data set to the same size.



we firstly partitioned the raw data set into several subsets. The driving route was divided into 50 road segments according to their location distribution. And then the whole data will be divided according to their belonging road segment (each data points contain the GPS position). As each road segment contains a different number of data points, we needed to calculate each segment's minimum datasize Sn. For example, S1istheminimumdata size of the first road segment (calculated from the entire dataset associated with the first road.
segment). Each dataset allocated to road segment 1 is thencompressed to sizeS1. After data compression, each data set will have the same data size Sall, as shown in equation (1):
In contrast to using maximum information entropy to select the size limit of the data, as in our previous study [39], the data compression method adopted in this paper allows us to retain most of the data points.

4. PREDICTION OF SHORT-TERM FUEL CONSUMPTION USING LSTM

The clustering-based method proposed in Section IIabove can only provide relatively long-term (25 to 35 minutes) assessment of the impact of a driver's behavior on fuel consumption. When attempting to perform relatively short-term prediction (30 seconds to 5 minutes), the clustering-based method does not work well for classifying driving behavior according to fuel efficiency. Besides, our clustering method is, in fact, a kind of classifier, so it has no prediction ability. Therefore, in this section we propose the Use of a time series learning method (an LSTM network) to model the relationship between driving behavior and fuel consumption, allowing us to predict the short-term fuel consumption

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state of a driver's behavior. As a driving behavior pattern represents the driver's interaction with adynamic driving environment, and fuel consumption can be treated as the cost result of this process, in this section we add dynamic driving environment information to our learning data.

3. TIME-SERIES DATA CONSTRUCTION

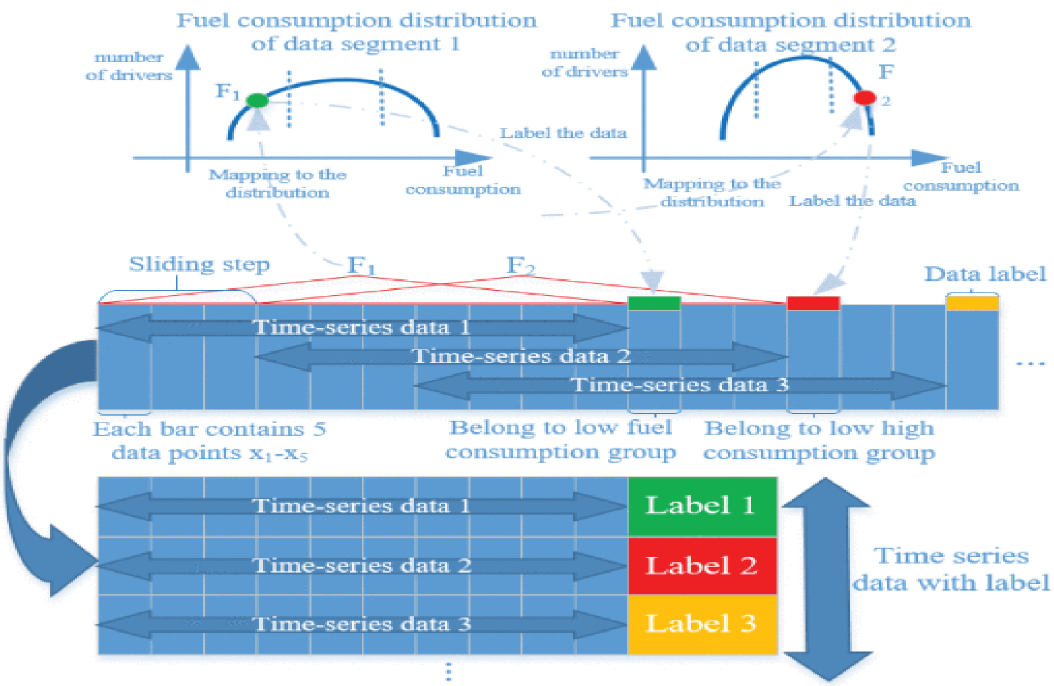
A. CODING OF ENVIRONMENTAL FACTORS:

As explained in our previous study[49], we divided the environmental factors intotwo categories, dynamic environmental features (other vehicles, brake lights of leading vehicles, pedestrians, etc.) and static environmental features (features which remaininvariable for relatively long periods of time, including road structures such as intersections andcurves).ThedrivingenvironmentfactorsusedfortrainingourmodelareshowninTable
1. Some of the dynamic features are captured by a camera mounted on the vehicle. As shown inFigs. 2and16, two types of roads were used in this study. In Fig. 16, the gray car is the experimental vehicle, the red vehicle is the leading vehicle or leading vehicle in the rightlane, the blue vehicle is a parked vehicle, the green vehicle is the first on-coming vehicle in the oppositelaneand the yellow vehicleis thesecond on-comingvehiclein the oppositelane.

$$S_{all} = \sum_{i=1}^{50} S_i$$

In ordinary-road scenes (one lane in each direction), the motorcycle or motorbike and the pedestrian are also considered to be environmental factors which can affect the driver's behavior. Thanks to the development of object detection technology, we can easily extract these traffic environment factors. In this studywe used YOLOv3 [50], a deep learning-based, real-time object detection method, to obtain the relative positions of these traffic factors. Using this position information, we can code the traffic factors into a digital form.

B. FUEL CONSUMPTION FEATURE LABELING AND TIME SERIES DATA CONSTRUCTION:



In BTrepresents the driving behavior data set from one trip along the fixed driving route, while S represents the size of the data (the number of behavior data points) collected during the time period it took to complete the route. S is calculated by applying the method showninFig.7 (compression of all of the datasets into the same size). The only difference in compressing process used in this section is that here, we divide the experimental road into

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150segments instead of 50 in order to obtain much more detailed data features.N in(16)represents the driving behavior categories strongly and moderately correlated withfuel consumption (N = 6).

METHODOLOGY:

The system has two modules, one being candidate oriented and the other module is organization oriented. In the first case the system would enable the candidate to give thetest for a particular company and also view the results of their previous tests which would help them to improve their performance. In the second scenario, the specifications and requirements of available job positions would be posted by the recruiter and the candidates can apply for the same by appearing for the required test.

IV. IMPLEMETATION

IMPLEMENTATION

4. **Train model class:** In this model class we have two method so working which involve giving instruction to the model and anticipating the result by providing different values.
5. **Train method**: The train method looks through CSV file with the dataset for trainingthe algorithm and set up a model using Logistic Regression.
6. **Testmethod**: The testmethodistoanticipatethe personality by passing anarray of values containing gender, age ,and the other five personality characteristics.
7. **Main Method:** The main method starts by creating an object of the train model class and the instructs the model by referring to the class's train method. The next step is to initializeavariablewithaToobjectandoutlinethesystem'sandingpagewithlabelsanda press. A button is created called Predict Personality, which refer so the predict person process.
8. **Predict Person Method:** The predict person method closes the rootTo inter window and setup a new top-level window with the relevant size and attributes. After this window' shading is labelled, followed by different labels and their entries. For choosing resume file
9. ,the candidate must press the Choose File button, which then calls the Open file process, which requires a button argument. For predicting the personality numerous entries areused in the predict person system. By pressing the submit button, all of the valuesurpassed to the prediction result.

V. FUTURE ENHANCEMENT

In the future ,we can improve the dataset so that the model will give more appropriate results .We can also integrate an SMS service into our system so that the users can getupdates on the latest job openings. Recruiters can also use our system as a job recruitment platform.

VI. CONCLUSION

In concluded unsupervised machine learning method of spectral clustering to classify drivers into three groups using six driving behaviour-based fuel consumption features. We then analysed the macro-behaviour of each group, focusing on power demand (speed and acceleration) and control stability (variation in speed and acceleration). Our results showed that the proposed spectral clustering-based method could accurately identify drivers with different fuel consumption profiles, and clearly modelled the relationship between the real- world driving data and the corresponding fuel consumption features. In addition to the estimation of fuel consumption using vehicle operation data, we also performed a qualitative analyses of driving behavior. Speed and acceleration information reveal the amount of power demanded by a driver, while variance in speed and acceleration represent the range of dynamic control exercised by drivers [25],[26]. The results of our analysis showed that high fuel consumption drivers (those in the red cluster) tend to maintain a relatively steady, high demand for power, while their dynamic control of the vehicle is less stable.

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