Driving pattern analysis to determine driver behaviours for a local authority based on the cloud using OBD II

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Abstract *– Aggressive driving is the leading cause of road accidents, which mainly results from driving behaviour that endangers drivers and the people around them. Such driver behaviours should be identified by local authorities to correct the behaviours or understanding the root cause of accidents. Data recorded using the On Board Diagnostic (OBD) II device can be analyzed to determine such behaviours. A sudden change in the manoeuvring of a vehicle indicates aggressive driving behaviour, which eventually yields non-uniform parameter values returned by the engine control unit (ECU) system without any specific reason. In this study, real-time data were recorded from ECU by using OBD II and an accelerometer. Artificial Intelligence was used to group different types of data to identify behaviours based on the similarity of data points. This study aimed to identify such drivers and reduce the risk of accidents. Driving behaviours were categorized as bad, normal, and aggressive. Because clustering is based on crowded data, which signifies similar driving patterns most of the time in the course of recording, this study used density-based spatial clustering of applications with noise unsupervised learning algorithm. The system sends data to the cloud, enabling the authorities to access it from any place for further action. ANOVA was conducted using IBM's Statistical Package for Social Sciences to compare and determine the most favourable method to collect data.*

Keywords*: Statistical Package for the Social Sciences, Engine Control Module, On Board Diagnostic II, Electronic Control Unit, Controller Area Network*

1. INTRODUCTION

Vehicles are equipped with many sensors that provide beneficial real-time information, such as that on speed, rpm, acceleration, and fuel consumption. Moreover, these data reflect the vehicle's condition and driver's behaviour. Previously, cars used On Board Diagnostic (OBD) I instead of OBD II protocols. OBD I protocols are manufacturer specific. The port and scanner differ for varying companies. This inconsistency led to the development of generic OBD II protocols. This study identifies the driving behaviour based on the driving pattern, considering engine OBD II parameters. Moreover, this study analyses the driving pattern based on OBD II data, such as speed and rpm. The findings of this study can help determine the previous driving behaviour and accordingly design measures based on travel history.

The direct association of driving behaviour with the driving style should be examined because it affects a vehicle's fuel consumption, emission, and safety. The OBD [1] helps to collect real-time data for post-analysis. The California Air Resources Board and the United States Environmental Protection Agency developed the OBD. The Society for Automotive Engineers and International Organization for Standardization standardized the OBD in the United States and worldwide. The iSaddle OBD-II scanner as shown in Fig. 1 has a small blue tooth adapter that supports all OBD II protocols [2]. We can determine a vehicle's protocol by examining the data link connector pinout as shown in Fig. 2. The CAB bus uses a differential signal system instead of a binary system as shown in Fig. 3.

The physical layer of the CAN Bus protocol uses differential transmission on a twisted pair medium. The messages are of eight data bytes and are protected by a checksum. No exact address is provided in messages; each message has a numeric value that controls its priority on the bus and may identify its contents. The lower the numerical ID in the message format is, the higher the message priority.

Secure communication channels should be ensured for data transfer. Databases placed on file servers should be protected, and users that possess and use those data should be controlled. Technical security solutions for physical and software protection with security procedures for redundancy and backup automation should be of high quality. However, the ongoing cyber war is still not suppressed. A possible reason for this is technical security solutions because they rarely consider the effect of the human factor on the security level of the system.

The human factor is the weakest element in the security chain because the internal threat is among the top information security problems [1].

Empirical studies examining the amount of human influence in the field of IT security are lacking [18]. Some existing empirical studies have analyzed user perception, behaviour, and attitude towards computer ethics and information security [3-5] because computer security and ethics are the essential components of a management information system [6].

Fig. 1. iSaddle OBD II Scanner

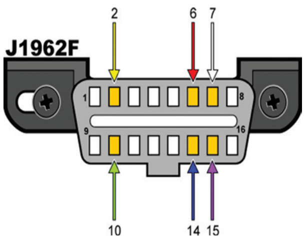


Fig. 2. Pinout diagram of OBD II port

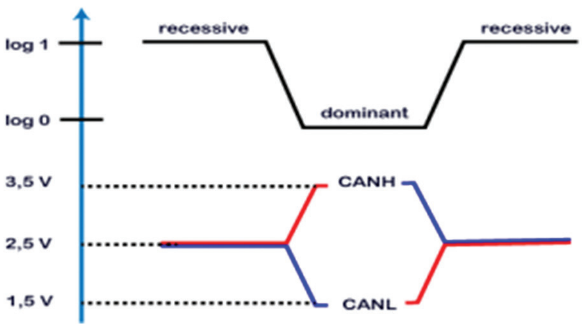


Fig. 3. Dominant and recessive CAN Bus signals

Bit-wise arbitration of the CAN-ID can resolve network access conflicts. All connected nodes observe the bus level bit-for-bit. All nodes transmit a recessive level and detect a dominant level, lose bus arbitration, and transit into the listening mode.

Fig. 4 presents how the ECU continuously broadcasts different sensor signals on the CAN bus identified by CAN ID (Standard ID is a hexadecimal value) that addresses the data and priority of arbitration. The lower the value is, the higher the priority. The data length is provided in bytes, and the data are also provided in bytes. The raw data are extracted by coupling the microcontroller with MCP2515 IC and the vehicle's OBD II port. Fig. 5 presents the equipment setup and connection.

```
13:46:53.432 -> Entering Configuration Mode Successful!
13:46:54.057 -> Setting Baudrate Successful!
13:46:54.057 -> MCP2515 Initialized Successfully!
13:46:54.057 -> MCP2515 Library Receive Example...
13:46:54.057 -> Standard ID: 0x158    DLC: 8  Data: 0x00 0x000x000x000x000x000x00 0x0A
13:46:54.057 -> Standard ID: 0x17C    DLC: 8  Data: 0x00 0x000x000x00 0x10 0x00 0x00 0x03
13:46:54.057 -> Standard ID: 0x158    DLC: 8  Data: 0x00 0x000x000x000x000x000x00 0x19
13:46:54.057 -> Standard ID: 0x1AB    DLC: 3  Data: 0x00 0x00 0x5D
13:46:54.057 -> Standard ID: 0x294    DLC: 8  Data: 0x00 0x000x000x00 0x48 0x89 0x00 0x1B
```

Fig. 4. Sample CAN raw data

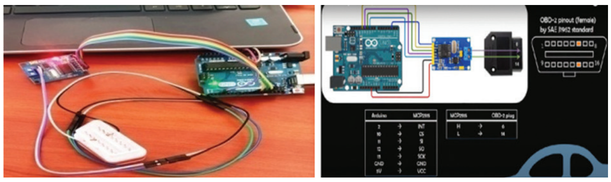


Fig. 5. Arduino, MCP, and OBD II setup

2. RELATED WORKS

Kawtar et al. described the vehicle-, management-, and driver-oriented classes of application. They mainly focused on the driver-oriented class [3], which comprises accident prevention, driving style assessment, and driver intent prediction. They used descriptive statistics and Bayesian classifiers to present the results. Peppeset al. [4] described a platform that combines machine and deep learning algorithms utilizing clustering techniques together with open-source-based tools to gather, store, process, analyze, and correlate different data retrieved from vehicles.

Navneeth et al. [5] examined the driver's profile and behaviour. Ameen et al. [6] identified driving behaviours to reduce the risk of accidents based on real-time data recorded from vehicles and reference data provided by previous researchers. The t-test was used to compare mean values between groups, and statistical analyses were performed using Statistical Package for the Social Sciences (SPSS).

Shaikh et al. [7] developed an Android application to alert any abnormality or anomaly in driving behaviour by using OBD II with Bluetooth and a Wifi connection. Hermawan et al. [8] examined driving behaviours and various methods to obtain OBD-II data for analyzing, modelling, and evaluating systems. Pan et al. [9] used the logistic regression model and examined behavioural parameters that affect a vehicle's risk situation and factors that affect safe driving. Ameen et al. [10] determined driving data, such as speed, rpm, and throttle position, by using OBD II. They proposed a method to develop a driving behaviour classification by using severity stratification of the acceleration model to determine safe driving. They mentioned an acceleration level of approximately ±2 m/s^2 for safe driving behaviour and ±4 m/s^2 for aggressive drivers with a risk of collision. Uvarov et al. [11] identified drivers with sensors listed in SAE J1979 specification, but the accuracy declined by approximately 15%. Sivaraj et al. [12] compared the standard limits of different OBD II parameters, such as speed, acceleration, retardation, and jerk. The telegram application they developed notified of any deviation observed in the driving behaviour. Jiang et al. [13] used a GPS-enabled smartphone app with a zero-inflated negative binomial regression model to investigate drivers' overspeeding violation behaviour for safety diagnosis and traffic warnings. Zhang et al. [14] analyzed the driving behaviour by using sparse automatic encoders and explored data to detect abnormal and aggressive behaviour. Regression analysis was performed to investigate the relationship between aggressive driving and road facilities.

Xiang et al. [15] proposed a new hybrid model consisting of cloud and the Elman neural network (CM-ENN) for predicting dangerous driving behaviour based on vehicle motion state estimation and passengers' subjective feeling scores. Dixit et al. [16] developed an OBD II vehicular data acquirement and analytics system for trip analysis and vehicle diagnostics and to monitor real-time driving behaviour based on cloud data. Jeon et al. [17] used LoRa communication to transmit vehicle operation information periodically to the server for analysis.

Meseguer et al [18] designed a real-time monitoring application to examine the correlation between the driver's physiological and the vehicle's diagnostic data. He et al. [19] mounted OBD II devices in HDVs in China to gather high-precision and sampling frequency data for verification. A driving behaviour portrait approach was proposed based on the driving behaviour and frequency and ranking of drivers' typical driving patterns. Agrawal et al. [20] proposed an analytical solution by using cluster analysis to detect safe or rash driving behaviour. Sonawane et al. [21] developed a framework that can be used for the clustered analysis of driving patterns by using data acquired from the OBD-II device. Massoud et al. [22] developed serious games (SGs) for obtaining information on drivers' trips by using a human driving profiling algorithm. Their developed system helped the driver in determining fuel efficiency. Trindade et al. [23] gathered data from vehicles' and smartphones' sensors. Their application enabled the evaluation of driving behaviour.

Fu et al. [24] developed the driving behaviour risk prediction neural network for prediction based on distracted driving behavioural data.

Mohammed et al. [25] compared driving behaviour between day and night, between weekends and weekdays, and among different road types (east, north, and south). They used the digital dashboard GPS pro app to collect data. The independent t-test and one-way ANOVA were used to analyze data. Alluhaibi et al. [26] proposed several methods to detect driving behaviours and identified each method's advantages and disadvantages. Wang et al. [27] used machine learning techniques to investigate drivers' behaviours in different traffic scenarios.

3. METHODOLOGY AND RESULTS

The app stored data in the Firebase cloud in the csv format. A part of the sample data is presented in Table 1.

Table. 1. Driving dataset

Device Time (sec)	G(x)	G(y)	G(z)	Speed (GPS) (km/h)	Speed (OBD) (km/h)	RPM
0	-3.3	3.59	6.02	12.58	10	783
1	1.35	2.67	9.05	11.79	10	783
2	1.17	2.49	9.57	11.11	10	784
3	1.45	2.27	9.76	10.62	9	812
4	1.34	1.88	9.57	10.17	9	1437.5

ANOVA was used to determine the most favourable approach to gathering driving data [28]. IBM's SPSS was used to compare means between groups for the same continuous dependent variable. The independent sample t-test was conducted to compare the sample mean values between the two groups. In the case of more than two groups, we used one-way ANOVA because it has one independent variable for which three sample data at three times points for three vehicles can be gathered. The sample groups were labelled 1, 2, and 3, respectively, and the dependent variable was speed. Table 2 presents the means, standard deviations, and standard errors of different sample data computed using SPSS. No significant differences were observed in data collected from various sources. The findings of the test of homogeneity of variance for different samples are presented in Table 3.

Table 2. Description of car speeds

Descriptives								
Speed								
					95% Confidence Interval for Mean			
	N	Mean	Std. Deviation	Std. Error	Lower Bound	Upper Bound	Min	Max
1	152	.4290	.20266	.01644	.3966	.4615	.21	1.00
2	209	.4425	.24985	.01728	.4084	.4765	.00	.97
3	108	.4823	.16368	.01575	.4510	.5135	.15	.79
Total	46	.4473	.21799	.01007	.4275	.4671	.00	1.00

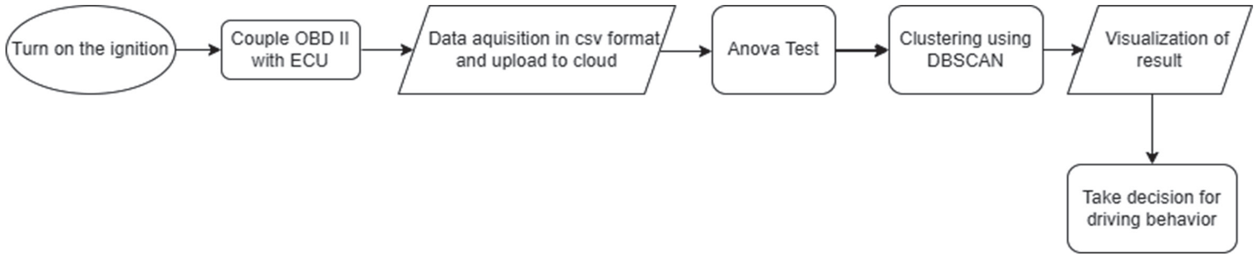


Fig. 6. The workflow design

One-way ANOVA was performed to compare speeds among groups 1, 2, and 3.

Table 3. Homogeneity of variances

Tests of Homogeneity of Variances					
		Levene Statistic	df1	df2	Sig.
Speed	Based on Mean	22.540	2	466	<.001
	Based on Median	20.792	2	466	<.001
	Based on the Median and with adjusted df	20.792	2	401.428	<.001
	Based on trimmed mean	22.841	2	466	<.001

The test was conducted by comparing the variation between the sample means and variation within each sample by using the following formulations. The difference in the group means was tested by partitioning the total variation into two components.

Fig. 6 presents the workflow design. The design methodology involved data acquisition from the ECU y using an OBD II scanner connected to a smartphone with Bluetooth and uploading the data to Firebase cloud storage. ANOVA was performed to examine captured data, and an unsupervised learning algorithm was employed to visualise behavioural data.

Variation of group means from the overall mean was calculated asthe $\bar{y}_{.j}$- $\bar{y}_{..}$ (variation between groups), where $\bar{y}_{.j}$ is the sample mean of group j and $\bar{y}_{..}$ is the overall sample mean. Variation of observations in each group from their group mean estimates, y_{ij}- $\bar{y}_{.j}$ (variation within group).

$$\sum_i \sum_j \left(y_{ij} - \bar{y}_{..}\right)^2 \tag{1}$$

$$\sum_{j=1}^{k} n_j \left(\bar{y}_{.j} - \bar{y}_{..}\right)^2 \tag{2}$$

$$\sum_i \sum_j \left(y_{ij} - \bar{y}_{.j}\right)^2 \tag{3}$$

ANOVA partitions the total sum of squares (SST) in eq. 1 into the sum of squares due to the between-group effect (SSR), as shown in eq. 2, and sum of squared errors (SSE), as in eq. 3.

$$\sum_i \sum_j \left(y_{ij} - \bar{y}_{..}\right)^2 = \sum_{j=1}^{k} n_j \left(\bar{y}_{.j} - \bar{y}_{..}\right)^2 + \sum_i \sum_j \left(y_{ij} - \bar{y}_{.j}\right)^2 \tag{4}$$

where

$$SSR = \sum_{j=1}^{k} n_j \left(\bar{y}_{.j} - \bar{y}_{..}\right)^2 \tag{5}$$

$$SSE = \sum_i \sum_j \left(y_{ij} - \bar{y}_{.j}\right)^2 \tag{6}$$

$$SST = \sum_i \sum_j \left(y_{ij} - \bar{y}_{..}\right)^2 \tag{7}$$

Where,

n_j is the size of the sample.

k is sample no

$df_{between}$(Degree of freedom) = k-1

df_{within}(Degree of freedom) = n-k

$MS_{between}$(Means Square) = SSR/$df_{between}$

MS_{within}(Means Square) = SSE/df_{within}

F(Anova coefficient) = $MS_{between}/MS_{within}$

Sig. was calculated from the F distribution table for the two degrees of freedom and F value.

No significant differences in Sig.'s values were greater than 0.05 as given in Table 4.

Table 4. ANOVA Test

ANOVA					
Speed					
	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.188	2	.094	1.982	.139
Within Groups	22.052	466	.047		
Total	**22.240**	**468**			

The post hoc tests indicate the values of Sig. after comparing with the values of one group with the other two groups as shown in Table 5; these values differed significantly.

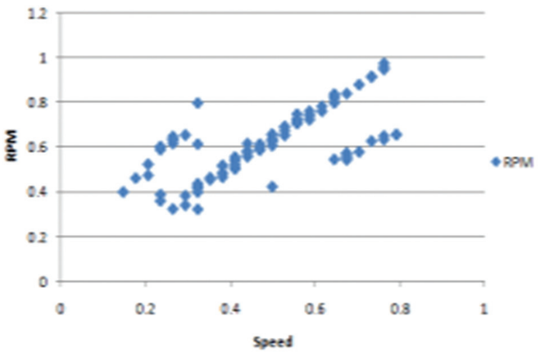
Three driving experiments were conducted in the city area by using three vehicles. The scatter plots are shown in Fig. 7(a), 7(b), and 7(c), and tests were conducted to measure the consistency of the data collected from the cloud. In this experiment, Honda Brio, Hyundai Accent, and Tata Tiago were tested under different traffic conditions.

We observed some pattern similarities and deduce behavioural outcomes from these patterns.

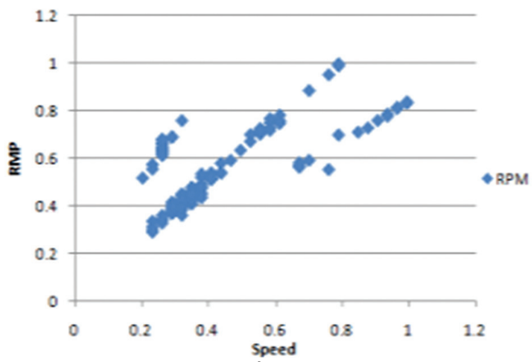
Table 5. Post Hoc Tests

Post Hoc Tests / Multiple Comparisons						
Dependent Variable: Speed						
LSD(Least Significant Difference)						
					95% Confidence Interval	
(I) Cars	(J) Cars	Mean Difference (I-J)	Std. Error	Sig.	Lower Bound	Upper Bound
1	2	-.01341	.02319	.563	-.0590	.0322
	3	-.05321	.02738	.053	-.1070	.0006
2	1	.01341	.02319	.563	-.0322	.0590
	3	-.03980	.02578	.123	-.0905	.0109
3	1	.05321	.02738	.053	-.0006	.1070
	2	.03980	.02578	.123	-.0109	.0905

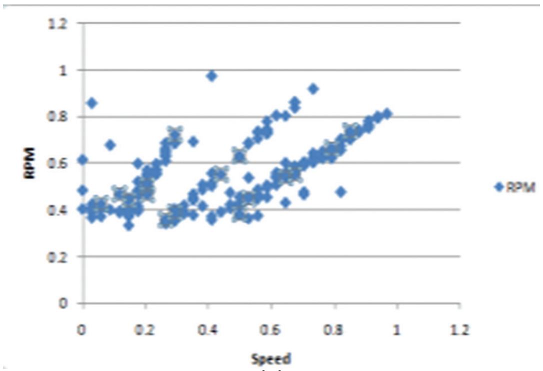
In the three figures, speed is plotted on the x-axis and rpm on the y-axis. A major concentration of points was noted in the three groups except for some outliers, which eventually led to three patterns of driving.



(a)



(b)



(c)

Fig. 7. Scatter plot of sample data

The dataset underwent a MinMaxScaler operation of Python. It returned a default value from 0 to 1 for both axes and preserved the original shape of the distribution of the dataset used. This process did not modify any information embedded in the original dataset. Moreover, the MinMaxScaler did not reduce the importance of outliers and noise.

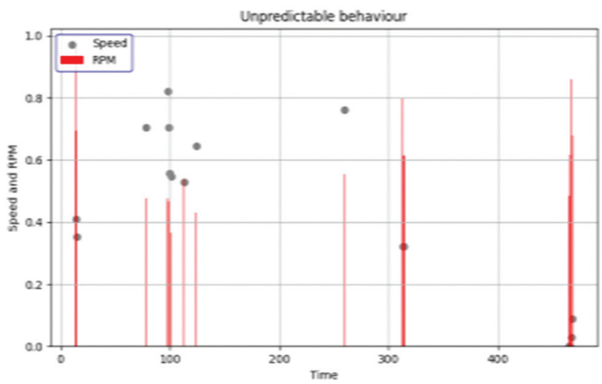
```
Total clusters in DBSCAN are= [-1  0  1  2]
Silhouette Score with 4 clusters is 0.41143794599627603
Intercept= [0.71741061] Coefficient= [[-0.30420312]]
Intercept= [0.27213606] Coefficient= [[1.32800002]]
Intercept= [0.01722772] Coefficient= [[1.24074742]]
Intercept= [0.02389404] Coefficient= [[0.8126347]]
```

Fig. 8. Clustering and regression parameters

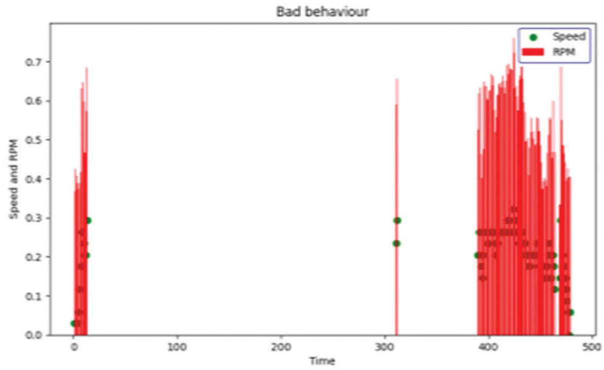
A linear regression line was fit using Python machine learning for different clusters given by various data frames, and we examined the nature of these regression lines. The coefficients and intercepts of these lines are presented in Fig. 8.

The −1 element in the list of the clustered output denotes outliers whose values are unpredictable, and regression coefficients had a negative value and a higher intercept. The remaining intercepts were small near zero when x was equal to 0. The positive coefficient value indicated an increase in rpm caused an increase in speed. The clusters were composed of different driving patterns, which depicted other driving behaviours, and regression lines were fitted with clustered points for each pattern. As presented in Fig. 9(a), 9(b), 9(c), and 9(d), driving patterns were classified as unpredictable, bad, normal, and good, respectively. The silhouette score was computed to test the accuracy of clusters. Normal, good, bad, and unpredictable driving was based on the speed and rpm of OBD II data recorded and eventually affected by comparative fuel consumption, which depends on throttling.

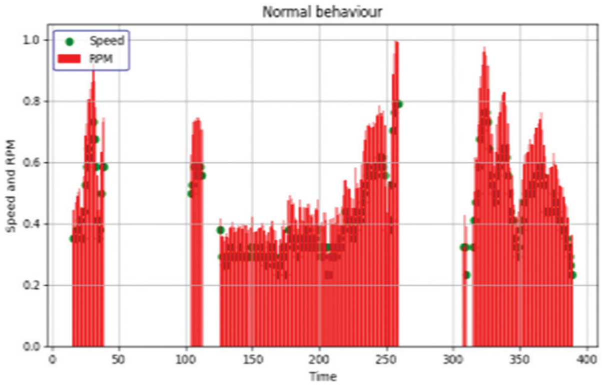
As presented in Fig. 9(e), the green marker represents speed and the red marker shows rpm. Driving behaviours were visualised on the basis of the relative positions of one marker above or below the other, as indicated in the algorithm.



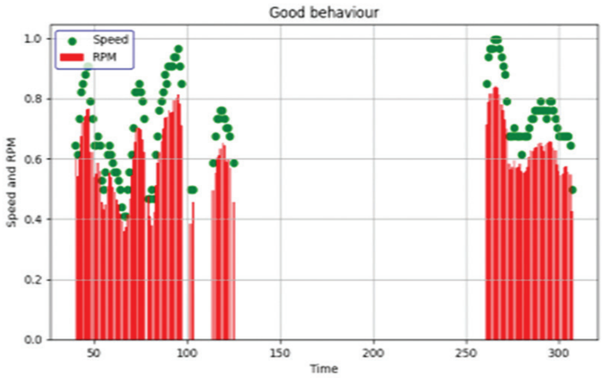
(a)



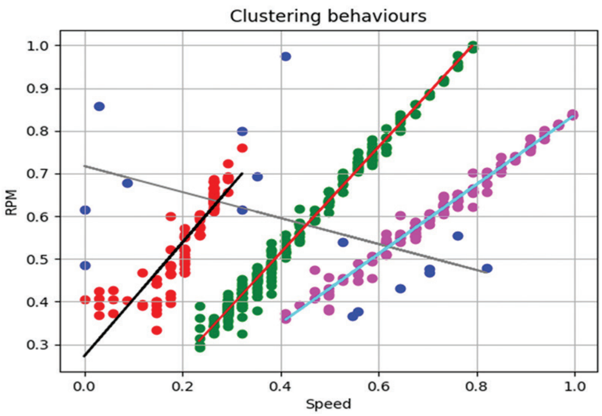
(b)



(c)



(d)



(e)

Fig. 9. Visualisation of driving behaviours

From the workflow design mentioned in the methodology section, driving behaviours can be computed as a function f(x,y) at time t on x and y for speed and rpm as

$f(x_t, y_t)$ = Unpredictable , if $x_t \not{R} y_t$

Bad, if $x_t << y_t$

Normal, if $x_t \approx y_t$

Good, if $x_t >> y_t$

We determined different driving patterns mathematically by using the aforementioned function and graph presented in Fig. 9(e).

4. CONCLUSION

Real-time OBD II data were gathered over a long period and sent to the server. Some of these analyses were performed within the app. Complex analyses were performed at the backend, that is, the cloud server. Data were forwarded to Firebase cloud storage. Once gathered data were received by the local authority or owner of the vehicle, they could determine the driver's behaviour for further action or reform the driver. The analysis can be conducted at the app level without the need to send the large data to the server. The analysis could be performed using the app, and only the resultant behavioural information was forwarded to the concerned party. This process can reduce the large size of OBD II data sent to the cloud.

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