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Department of Computer Science and Engineering

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Final Year Project Report

Driver Behavior Analysis using Vehicular Data

Project Group 15

K.A.De Zoysa Karunathilaka	120089X
P.U.Jayaweera	120273G
K.G. Kalani	120281E
R.W.P.M. Meththananda	120394D

Supervised by

Dr. H.M.N. Dilum Bandara

Coordinated By

Dr. Charith Chithraranjan

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Declaration

We, the project group 15 (K.A.De Zoysa Karunathilaka, P.U. Jayaweera, K.G. Kalani, R.W.P.M. Meththananda under the supervision of Dr. H.M.N. Dilum Bandara) hereby declare that except where specified reference is made to the work of others, the project “Driver Behavior Analysis using Vehicular Data” is our own work and contains nothing which is the outcome of work done in collaboration with others, except as specified in the text and Acknowledgement.

Signatures of the candidates:

1.	K.A.De Zoysa Karunathilaka	120089X
2.	P.U.Jayaweera	120273G
3.	K.G. Kalani	120281E
4.	R.W.P.M. Meththananda	120394D

Supervisor:	Project Coordinator:
....	....
(Signature and Date)	(Signature and Date)
Dr. H.M.N. Dilum Bandara	Dr. Charith Chithraranjan

Abstract

Usage Based Insurance (UBI) is one of the emerging trends in the insurance industry, where the premium for the vehicle is calculated based on the driver's driving performance. However, driver profiling techniques typically used in UBI rely on simple attributes such as number of rapid breakings and are based on a small sample of driving within a week to a month. This neither produces a detailed profile of the driver nor ensures that the driver continues to drive safely after the sampling period. It could be more effective, if the driver can be monitored across several key attributes throughout the driving and feedback could be send to the driver to improve his/her driving habits. Expanded wireless broadband network access, emergence of Internet of Things (IoT), and data analytics provide the right combination for rich monitoring and driver feedback. Motivated by these concerns and emerging technologies, we focused on developing a driver profiling system for UBI by retrieving real-time vehicular data. Driver and location related data are collected through a Bluetooth-based On Board Diagnostic (OBD) dongle and smartphone. The collected data are then transferred to the backend using a Representational State Transfer (REST) API. Collected data are analyzed in both real-time and batch mode using WSO2 Data Analytics Server (DAS). The proposed system detects six types of abnormal driving behaviors in real-time and notify the driver. The persisted data is used to conduct historical analysis such as driver categorization (e.g., below normal, normal, abnormal, and risky), calculation of relative skill and aggression scores, as well as comfort and safety factors. Results of the analysis are then displayed on a dashboard using another REST API. Insurers may also use the same API to pull the driver profile data to other systems.

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List of Abbreviations

API	Application Programming Interface
ASA	Aggression Score Absolute
DAO	Data Access Object
DAS	Data Analytic Server
DPP	Driver Profiling Platform
GPS	Global Position System
HTTP	Hyper Text Transfer Protocol
HTTPS	Hyper Text Transfer Protocol Secure
JWT	JSON Web Token
ODM	Object Data Modeling
OSRM	Open Source Routing Machine
RAS	Relative Aggression Score
REST	Representational State Transfer
RPM	Revolution Per Minutes
RSS	Relative Skill Score
SDK	Software Development Kit
SSA	Skill Score Absolute
UBI	HTUser Based Insurance
UDF	User Defined Function

1. Introduction

1.1. Background

Though vehicles are becoming safer, risky driving behavior is on the rise. This is due to several factors such as fast-paced life where everyone is in a hurry, competition among drivers (e.g., buses completing to collect more passengers), insufficient road signs, deteriorating road conditions, negligence of law, higher number of novice drivers, and driving under influence. Risky driving is detrimental, as not only it leads to accidents, but also leads to increased insurance premiums for all drivers and low fuel efficiency. With ever increasing insurance premiums and the advancement of technology, insurance companies are now starting to offer Usage Based Insurance (UBI) [1]. UBI is based on the driver behavior, where a driver is ranked from low risk to high risk based on his/her driving style, time of day, and location. However, most UBI schemes are based on a multi-week, one time sample of driving behaviour such as hard braking and rapid lateral movements [2]. Hence, the drivers may follow a safer driving pattern during the sampling period, while they may adopt their natural behaviour once the sample is taken and discount is obtained for the insurance premium.

1.2. Motivation

With the current demand, UBI concept could be raised up, if an accurate driver rating method can be introduced. The drivers will not be able to fake the insurance companies by acting safer during the sampling period, as the insurance company can observe the driver behavior in real-time with the proposed solution. Moreover, when an unsafe driving behavior is detected, the driver could be immediately alerted reminding the driver to drive safe. Whereas long-term driving data analysis can also be used to educate on better driving habits that lead to safe and efficient driving. Furthermore, the accuracy of driver profiling and driver feedback could be improved by considering related factors such as current weather and road conditions. It is high-time to develop such a solution given the recent technological advancements in mobile computing, Internet of Things (IoT), wireless broadband, and data analytics. Such a solution could reduce road accidents while improving driver behavior and reducing costs.

1.3. Problem Statement

If a driver can be made aware about his/her abnormal driving behaviors, it will be helpful to reduce accidents and increase fuel efficiency. Moreover, insurance companies are now trying to adopt UBI, which calculates the premium based on the driver's driving behavior and time of driving because reckless driving badly affect the profitability of insurance companies. Therefore, it is essential to have a system that can accurately profile a driver based on his/her driving behavior using both real time and long term data, as well as other related vehicular and environmental data. Thus, the problem this project tries to address can be defined as follows:

How to profile a driver based on his/her driving behavior using both real-time and long-term data, as well as other related vehicular and environmental data?

1.4 Objectives

Develop a system for driver profiling and altering that is:

1. real time, where the process is based on live data rather than a data bundle collected during a sampling period. The system should be capable of identifying abnormal behaviors straight away.
2. accurate, where the system reveals the true nature of the driver. There should be no room for a driver to intentionally change the evaluation of the system other than changing his driving behaviors.
3. computationally efficient, where the system is capable of providing the service while maintaining the above two qualities with the minimum usage of the computational and bandwidth resources.

1.5 Outline

Rest of the report is organized as follows. Chapter 2 presents the literature review. The architecture of the proposed system with the key components is discussed in the Chapter 3. Implementation details are presented in chapter 4. Results are presented in chapter 5. Chapter 6 presents the performance and accuracy of the system. Conclusions and future work are presented in Chapter 7.

2. Literature Survey

Various literatures have introduced several driving behavior analysis methods based on the vehicular data and several implementations to analyze the driving behavior using vehicular data. Section 2.1 discusses a selected set of driver behavior analysis methods and implementations. When considering driving behaviors, certain driving behaviors are not very safe. Such unsafe driving behaviors are discussed in the Section 2.2. While implementing a driving behavior analysis system, vehicular and location data needs to be collected to analyze driving behavior. These data can be collected using smartphones or OBDII port in the vehicle. OBDII and GPS based area collection is discussed in Section 2.3. Section 2.4 present WSO2 Data Analytic Server (DAS) which can be used to conduct both real-time and batch data analysis.

2.1 Driver Behavior Analysis

2.1.1 Driving Behavior Analysis Based on OBD Data and AdaBoost Algorithm

Chen et al. [5] proposed a novel driving behavior analysis method based on the vehicle On Board Diagnostic (OBD) data and AdaBoost algorithms. Via OBD interface authors collect vehicle operational data, including vehicle speed, engine RPM, throttle position, and calculated engine load. The proposed method consists of driving operation acquisition module, data preprocessing module, and AdaBoost classification modules which can determine whether the current driving behavior belongs to safe driving or not. Driving behavior analysis data will be divided into training set and test set. Preprocessing and feature extraction are simultaneously applied to both sets. Classification makes the test samples into the driving model based on AdaBoost algorithms to classify and determine the test sample category.

Authors used three characteristics, i.e., the relative ratio of vehicle speed and engine speed, relative ratio of throttle position and engine speed, and the engine load to analyze whether the current state of the driving behavior is safe or dangerous. First, the proposed method computes the change rate of vehicle speed, engine speed, and throttle position as follows:

$$D(t) = (\mathrm{data}(t_2) - \mathrm{data}(t_1)) / (t_2 - t_1) \qquad (2.1)$$

where $t_2 - t_1 = 1$.

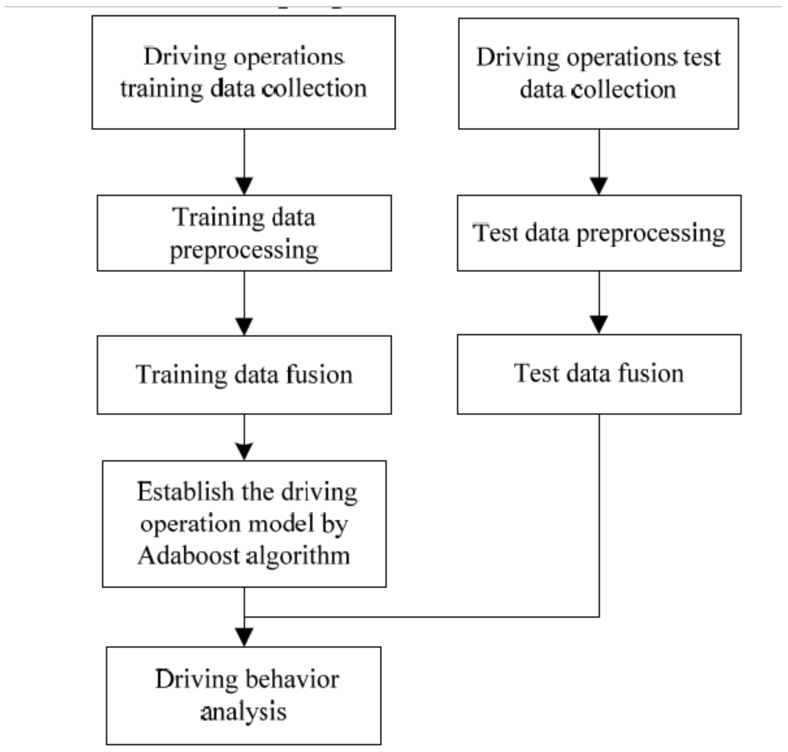

Driving operations training data collection
Driving operations test data collection
Training data preprocessing
Test data preprocessing
Training data fusion
Test data fusion
Establish the driving operation model by Adaboost algorithm
Driving behavior analysis

Figure 2.1: Flowchart of the driving behavior analysis method [5].

Then it computes the relative ratio of the vehicle speed and engine speed, the relative ratio of throttle position, and engine speed because there is lager difference between the values of vehicle speed, engine speed, and the throttle opening. Calculation is shown in Equation 2.2 and 2.3.

$$\mathrm{R}_{cz}(t) = (\ \mathrm{cs}(t) / 220\ ) / (\ \mathrm{zs}(t) / 8000) \qquad (2.2)$$

$$\mathrm{R}_{\mathrm{jz}}(t) = (\mathrm{jq}'(t) / \max (\mathrm{jq}')) / (\mathrm{zs}'(t) / \max (\mathrm{zs}')) \qquad (2.3)$$

where $R_{\mathrm{cz}}(t)$ is the relative ratio of the vehicle speed and engine speed, $cs(t)$ is the vehicle speed at time t with maximum speed of 220, and $zs(t)$ is the engine speed at time t with maximum engine speed of 8000. $R_{jz}(t)$ is the relative ratio of throttle position and engine speed, $jq'(t)$ is the change rate of throttle position at time t, $zs'(t)$ is the change rate of engine speed at time t, max(jq') and max(zs') are the maximum change rate values of throttle position and engine speed, respectively.

Finally, the proposed method combines these three feature values which are the relative ratio of the vehicle speed and engine speed, the relative ratio of throttle position and engine speed, and engine load to determine whether the vehicle data is normal or bad driving condition. Here authors have defined threshold values for each of these three features for normal and bad conditions.

Table 2.1: Threshold values for each feature.

Features	**Normal Vehicle Condition Data**	**Bad Vehicle Condition Data**
Relative ratio of the vehicle speed and engine speed	0.9 – 1.3	> 1.3 or < 0.9
Relative ratio of the engine speed and throttle valve	0.9 – 1.3	> 1.3 or < 0.9
Engine load	20% - 50%	> 50% or < 20%

Experimental results have shown the correctness of the proposed driving behavior analysis method can achieve an average accuracy rate of 99.8%under various driving condition simulations. In addition, they had said that using the real AdaBoost algorithm, the proposed method could obtain 100% accuracy rate under 15 iterations. This proposed method does not consider about the traffic condition, weather condition and the time in which the driver drives the vehicle. These factors also affect to the driving pattern; hence, important to be considered.

2.1.2. Abnormal Driving Detection using Real-Time GPS Data

An abnormal driving detection method based on real time GPS data is presented in [6]. Authors used vehicle speed, direction, and acceleration details to detect the abnormal behavior using GPS data. Authors collected a training data sample, analyzed those data and defined threshold values for vehicle speed, acceleration and the vehicle direction. To get the threshold value for vehicle direction, they had used steering wheel movement (SWM). SWM can be distinguished between small movement (1-5 degree) and large movement (6-10 degree). As 5 degrees and below is considered small movement, 6 degrees and above will be used as a threshold direction angle. According to the data of direction changing, the result shows for normal condition, some movement from right to left and then to right (RLR) and from left to right and then to left (LRL) movements were detected with a speed between above 0 km/h and above 50 km/h but no LRLR or RLRL movement detected above 30 km/h. So they had come up with a conclusion that abnormal driving will be detected if the driver turns left or right four times continuously with speed more than 30 km/h. While collecting the training data sample authors had considered about all traffic conditions and weather, day and night. After analyzing data, the abnormal driving detection algorithm was created using two parameters; position and velocity. Vehicle position or location determined by latitude, longitude and altitude while velocity is in speed (km/h) and direction degree. The algorithm had been developed generally by three behaviors which could contribute to abnormal behavior. Those three behaviors are sudden speed drop with high deceleration, speed increase with high acceleration, and unsmooth vehicle direction movements. They are calculated as follows:

Speed suddenly drop with high deceleration,

$V_n < V_{n-1}$ and $V_{n-1} – V_n > d$

where V_n is current speed, V_{n-1} is previous speed, *d* is deceleration threshold value.

Speed increase with high acceleration,

$V_n > V_{n-1}$ and $V_n – V_{n-1} > a$

where *a* is acceleration threshold *f*.

Unsmooth vehicle direction movements,

D1 > 0 and D2 < 0 and D3 > 0 and D4 < 0 and s > 30
or
D1 < 0 and D2 > 0 and D3 < 0 and D4 > 0 and s > 30

where D1 is Dn – D n-1, D2 is Dn-1 – D n-2, D3 is Dn-2 – D n-3, D4 is Dn-3 – D n-4, are all directions and *s* is speed.

All abnormal driving is detected in algorithm by considering current, previous, and historical data. Using this algorithm, abnormal driving behavior can be detected in real time. However, the proposed algorithm can be applied to detect driving above speed limit that they have proposed. In addition, this algorithm only considers about the vehicle movement of left or right four times. But there may be abnormal driving with the movement of left or right three times. This algorithm does not capture those scenarios.

2.1.3. Acceleration-Based Safety Evaluation Procedure for Smartphones

Rosolino et al. [7] proposed a prototype mobile application that can evaluate the grade of safety that drivers are maintaining on the road. Authors measure both the longitudinal and lateral acceleration and send a real-time warning to the user, if the driving behavior is not safe. This will help drivers to correct their driving style to be more safe and less aggressive. The user’s driving style analyzation was based on both longitudinal and lateral acceleration values that are derived from GPS position data. Here they have evaluated the aggressiveness by plotting vehicle’s acceleration on a g-g diagram where lateral acceleration displays on the horizontal axis and longitudinal acceleration displays on vertical axis (friction circle). In addition, they have plotted a g-g diagram for driving experiences too.

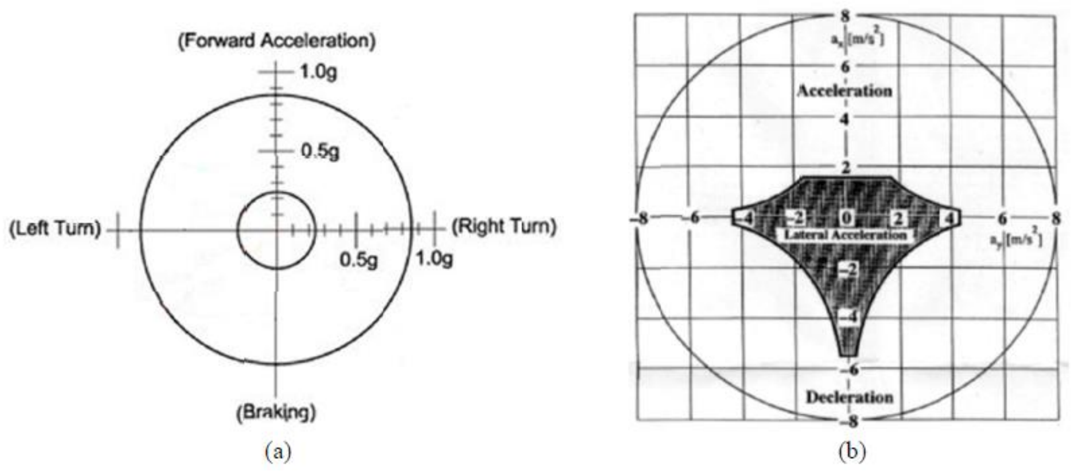


Figure 2.2: User's driving style; (a) Friction circle edge and (b) g-g diagram for driving experience [7].

By overlapping the diagrams of driving experience and the friction circle, a new area of safe driving has been identified. This new diagram has been named as Driving Safe Diagram (DSD).

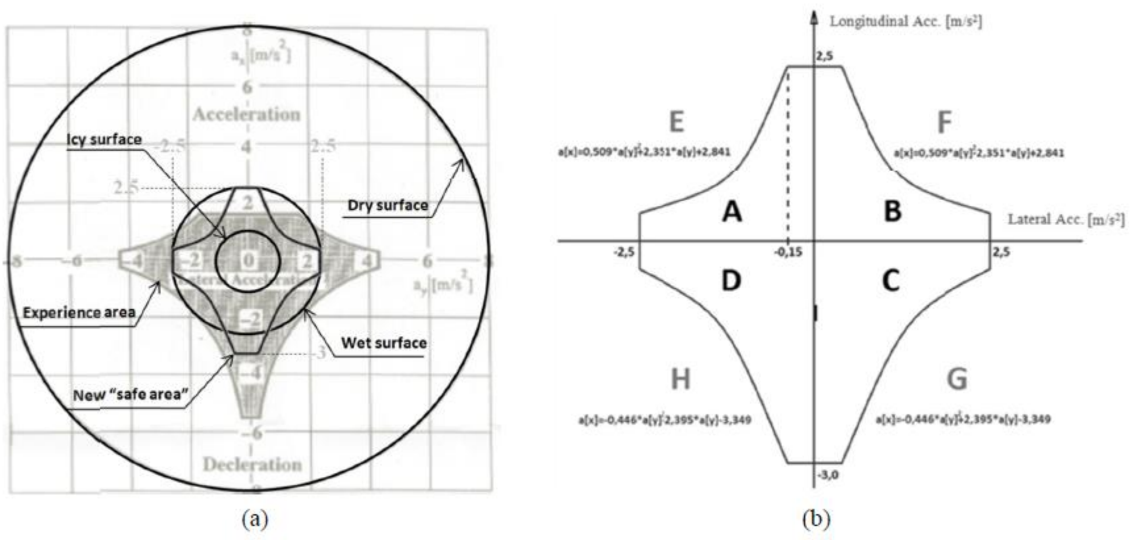


Figure 2.3: Driving safe diagram; (a) Construction of new "safe area" and (b) Driving Style Diagram (DSD [$a_x - a_y$]) [7].

Here authors have considered about the road conditions whether the road is dry, wet, or icy. According to their research, the new safe area has a limit of 2.5 ms^{-2} for both longitudinal and lateral accelerations and 3.0 ms^{-2} for deceleration. In the experiment, to identify the aggressive behavior, many potential dangerous events have been taken into account. Some of them include excessive speeds, higher than the law limits, sudden, intense and repeated braking and accelerations, aggressive left and right turns, aggressive U-turns and round about crossing, aggressive lane changes, etc. The behavior of each driver has been evaluated by calculating the percentage of points that are characterized by values of accelerations higher than the limiting edges of the DSD area. This proposed method has allowed to establish a specific threshold for this percentage. This threshold value has been used to develop a mobile application for a systematic control of vehicle acceleration during a specific period of time with the possible with the possibility of giving a continuous feedback to drivers. Experimental results showed that the best threshold value for distinguishing between aggressive and non-aggressive driving behavior can be set to 9% of external points.

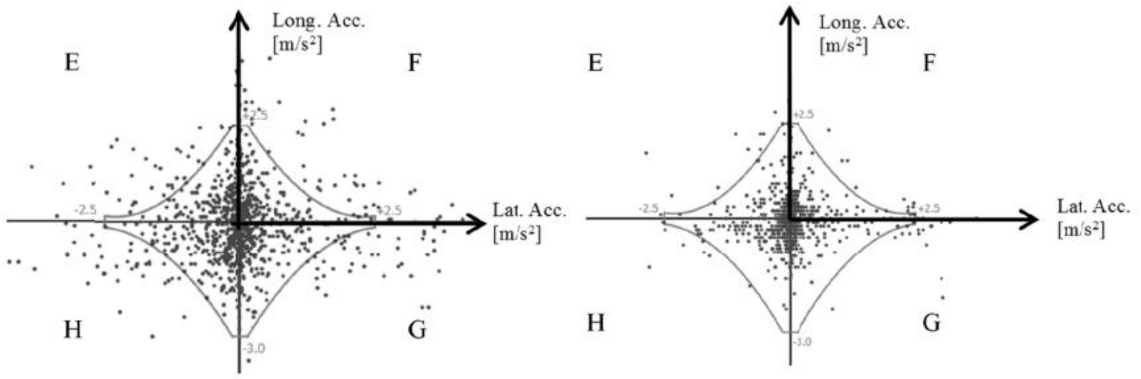


Figure 2.4: Distribution of points in the DSD for an aggressive driver (left) and a safe driver (right) [7].

While the proposed system considers about the road conditions (dry, wet, or icy), it does not consider about the traffic conditions. However, aggressive behavior could be impacted by traffic conditions because high traffic flows affect driver behavior in the passing maneuver, and induce the driver to adopt highly risky behavior. Hence, traffic conditions should be considered.

2.1.4. Driving Style Recognition Using Fuzzy Logic

A driving style recognition approach using Fuzzy Logic is presented in [8]. Authors proposed method recognize the driving styles: below normal, normal, aggressive and very aggressive based on the readings of 2-axis accelerometer and the speed that is integrated in most of the vehicle GPS trackers. All processing has been done on a web server. Here they have calculated Euclidean norm of the longitudinal and lateral acceleration and average of the norm has been combined with the speed of the vehicle to a fuzzy inference system to classify the driving style to below normal, normal, aggressive and very aggressive. Fuzzy inference system can be considered as an inference system that maps, by means of combination rules, input to output using fuzzy logic. Here as first input of the inference system, norm of the acceleration on longitudinal (forward and backward) and lateral (side to side) directions of the vehicle have been used and corresponding fuzzy values have been defined to be Low, Medium and High, the membership functions have been inferred Then as the second input, speed of the vehicle has been used and corresponding fuzzy values has been defined to be Very Low, Low, Medium, High and Very High, and corresponding membership functions have been inferred. Finally, the output of the system is the driving behavior, which is defined by four fuzzy values Below Normal, Normal, Aggressive and Very Aggressive. Then membership functions for that also have been inferred

The inputs and outputs membership functions and the fuzzy rules were tuned manually based the real test data and three expert drivers. Membership functions have been inferred from the analysis of a real data that recorded for normal and aggressive driving. This method has considered only about the longitudinal and lateral accelerations and the vehicle speed. It has not focus on the driving direction of the vehicle. Sometimes some drivers drive their vehicles in normal pattern but change the vehicle directions aggressive way. This method has not focused on that area.

2.1.5. Cloud-Based Driver Monitoring and Vehicle Diagnostic with OBD2 Telematics

Malintha et al. [9] proposed a cloud based vehicular data acquisition and analytic system for monitoring real-time driver behavior, trip analysis and vehicle diagnostics. This system consists of an On Board Diagnostics (OBD) port to Bluetooth dongle, an app running on a smartphone and a cloud-based backend. In addition, there is a Complex Event Processors (CEP) at both the smartphone and backend based on OBD data. This has been used to detect and notify unsafe and anomalous events in real time. The CEP at the smartphone alerts drivers about the rising coolant temperature and rapid drop of the fuel, provides trip logs and filter out messages to be sent to the backend, saving both the bandwidth and power. Backend CEP detects reckless driving in real time. In addition, backend uses historical data to detect driving anomalies and predict impending sensor failures. So the proposed system is capable of collecting, storing and analyzing vehicle data in real time as well as over a long period of time. The system has provided a set of data analysis tools for reckless driving and driving anomaly detection, vehicle sensor failure prediction, high fuel consumption and high coolant temperature alert generation and trip detail summarization. The proposed method monitors drivers to detect two driving pattern. One is reckless driving and other one is driving anomaly. The main deliverables to end users are the mobile app for Android devices and the web interface which displays monitored data and analyzed results. So the results of long-term analyses are displayed via a web interface and real time results like alerts are displayed in the mobile app.

2.1.6. MyDrive: Drive Behavior Analytics Method and Platform

Drive Behavior Analytics Method and Platform has been proposed a top quality system to monitor the driving style using a Skill Aggression Quantifier algorithm [9]. Here they are going to do the analyzing part according to the following three parts. Peer group analysis, Individual analysis and trip level analysis.

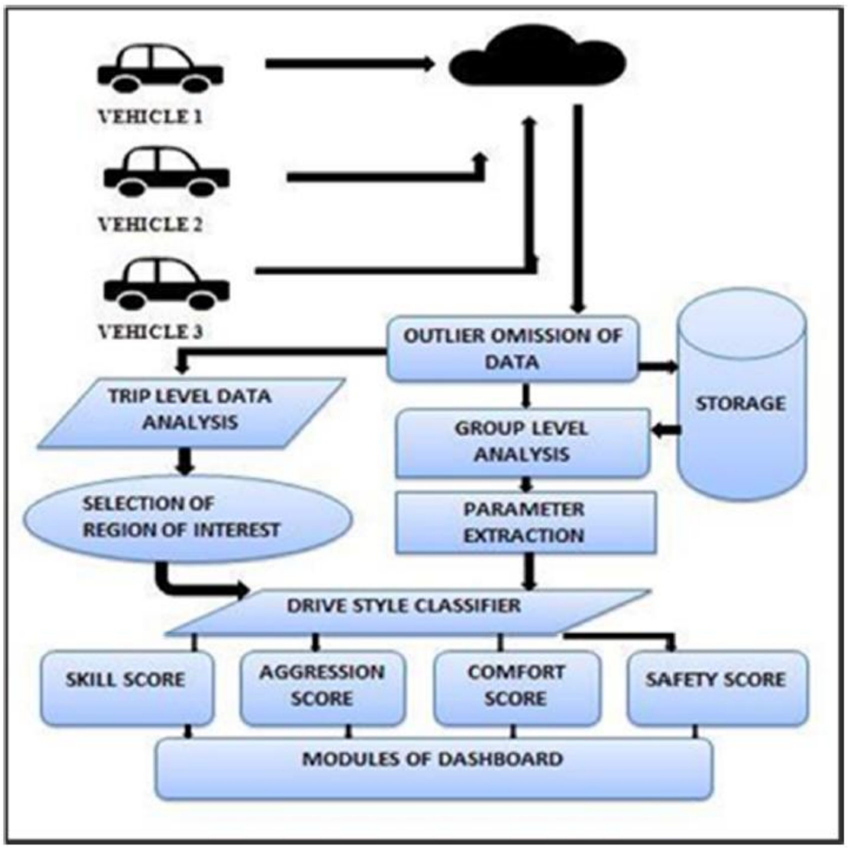


Figure 2.5: Platform description scenario [9].

In peer group analysis, they are going to analyze a particular driver based on a particular whole group data. After collecting those data, they compute some requested value from their proposed algorithm, Skill Aggression Quantifier and they categorize drivers based on following Rival, Cautious, Novice, Risky types.

Individual analysis part is going to be compared with two phases. Training phase and current phase are the labeled phase of the proposal. In training phase, authors consider first six or seven trips as initial model and further collected trip data would be compared with previously introduced model. Current phase is the phase that is going to be created a model with all trip data and then they are going to analyze particular driver based on that current trip level model. Here they are used some assumed threshold values. They are going to categorize driving patterns with above mentioned threshold values as follows:

- Hard acceleration > 2.74 ms^{-2},
- Hard deceleration < 2.74 ms^{-2},
- 0.1 ms^{-2} < Normal acceleration < 2.74 ms^{-2},
- -0.1 ms^{-2} < Normal deceleration < -2.74 ms^{-2}

In trip level analysis is going to manage all trip data and compare with current trip data.

In all step they are going to collect data using their proposed mobile system, named My Drive. Collected data is stored in cloud based network, analyze at the back end and display the statistically analyzed results on the dashboard as per request by the user of the platform.

2.1.7. Predicting Driving Behavior Concerning with Driver's Past Movements

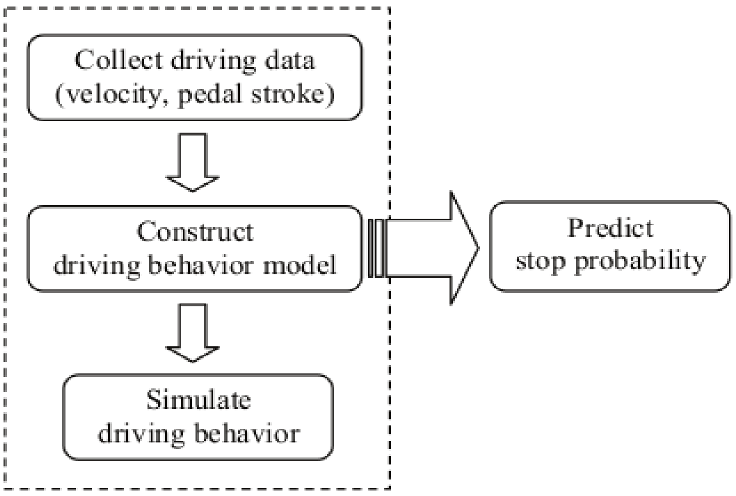

Collect driving data (velocity, pedal stroke)
Construct driving behavior model
Simulate driving behavior
Predict stop probability

Figure 2.6: Basic architecture for predicting driving behavior using past movements [10].

Another method for predicting driving behavior has been introduced [10] as a modeling method for predicting driving behavior concerning with drivers past movements. Here they have mainly considered about the past driving patterns of the drivers since they highly think that human’s behavior is strongly related to the past details. They mainly focused how to prevent accident by stopping vehicle before happening the accident. According to the proposed system, they need to monitor not only the moving speed and following details of the system using vehicle but also the vehicles that are closely driven for that particular vehicle. They are going to use radar sensor system to track following vehicle and leading vehicle moving patterns. To analysis this part, they are collecting velocity and pedal strokes as deriving data using driving simulator. They introduced Current Driving Trigger to consider the chain in dynamic flow of the past actions.

Because they only focused on stopping probability of the vehicle, there may some erroneous predictions since there are so many normally aggressive drivers, who are driving very close to other vehicle with some related high speed. But they are very accurate. But time passed, their model is getting improved and system would be accurate. Until that happen their proposed system is not an advanced one.

In addition to predict the happening an accident, they are going to monitor the drivers’ pattern and simulate the details and predict their next behavior. For that particular task, they are using Dynamic Bayesian Network which is structured on Auto Regressive Hidden Markov Model. These driving styles are going to recognize using decomposed fuzzy logic system as decision making process, used fuzzy logic model.

There are two parts in proposed system which are in vehicle embedded system and web based system while our system doesn’t have such vehicle embedded system and need only a OBD2 dongle to retrieve data from the vehicle engine and our system also has a web based analysis system with cloud storage to store collected data and store analyzed data. In-vehicle system contains GPS receiver to track the speed and locations, two axis accelerometer to track lateral movements. Such acceleration details are used to identify the sudden movements.

2.1.8. Driving Styles Recognition Using Decomposed Fuzzy Logic System

An advanced driving styles recognition system has been proposed here [11] which is enforced with fuzzy logic by enhancing the fuzzy logic concept. There are so many reasoning applications that are predicting the future happenings by using fuzzy logic. But, according to this proposed system, they have showed us, accuracy of the system with real scenarios than the traditional fuzzy logic system since this proposed system is used the decomposed fuzzy logic algorithm.

Dimension of this system can be considered as multidimensional system, since this system is considered so many conditions when reasoning an incident. They consider speed, acceleration and distance between leading and following vehicle. To obtain above data from the monitoring vehicle, they use some few gadgets while we are using only OBD2 dongle in our proposed system. They are using two radar sensor to get data about distance with leading vehicle and following vehicle. To obtain the acceleration details, they are using two dimensional accelerometers. We are also proposed 2D accelerometer which is embedded with OBD2 dongle to get sense about lateral movements. In addition to that they are using GPS module to get data related to the position and the speed while we are also using GPS tracker embedded with our OBD2 dongle. This system is manipulated by a microcontroller which is embedded to the vehicle. The consequences of the proposed system they need to add those gadgets separately for the system. But in our proposed system is only using OBD2 dongle which is really easy to apply for the system. they also using GPRS to communicate with cloud while we use little bit of GPRS as communication method as we are sending analyzed summary for the mobile application. This system can be considered as very close approach to our system but our system is little bit enhance since we are using weather conditions, road conditions and we are pitching the analyzed data to get Usage Based Insurance approach. Since they are using decomposed fuzzy logic system, they are using three separated model to analyze the speed, acceleration, distance. According to the analyzing part they are using following categories to categorize the monitored drivers' styles.

Further that, following rules will be based to the values of Membership function of fuzzy logic.

- Speed = low and acceleration = low and distance far – driving style = below normal.
- Speed = normal and acceleration = normal and distance = normal – driving style = normal.
- Speed – high and acceleration = high and distance = close – driving style = aggressive

Speed – very high and acceleration = very high and distance = very close – driving style = very aggressive.

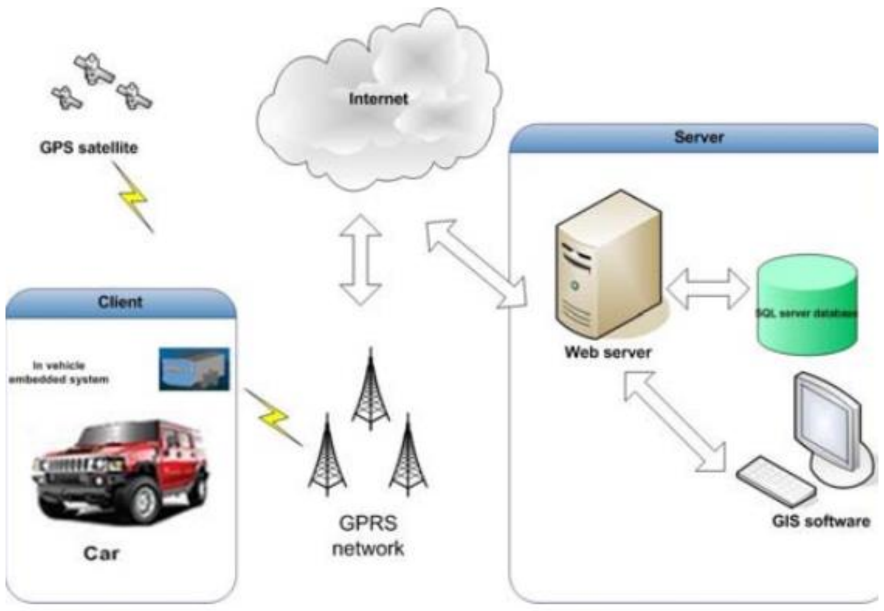


Figure 2.7: System Architecture Layout [11].

2.1.9. Reliable Method for Driving Events Recognition

This proposed system is really not a system that is going to analyze risky driving patterns. They are predicting next driving patterns based on GPS locations and previous data collections [12]. This can be really used as a model for comparing presenting behavior.

Here they are using Hidden Markov Model to recognize driving event. As well as they are using some embedded system which is contained Gyroscope, GPS tracker, 2D accelerometer. In this system data processing system is embedded with vehicle and no need to send to cloud. This concept is not reliable since storage capacity is limited and applying system is very expensive since customer must have to buy the computer parts also and need to attach it into the vehicle.

However, they are collecting data and processing to recognize the event. For that analyze part they are using Hidden Markov model. Here they are using some model such as previous data set, situation model and current building model. Using those models, they predict the next event of the driver and then they assess the prediction. According to the result their model is to be enhanced.

Some vehicles are routing their path in similar way. By tracking GPS location, system can predict the next driving event based on previous data. By comparing the result, we are able to recognize who is the driver since driving pattern is very unique from driver to driver. Otherwise we can predict they are not under the normal behavior at the moment by comparing the result and predictions.

Moreover, they are proposing to normalize collected data. This would be really helpful since data storage should be efficient in this system because they are not going to use cloud based method. But our proposed system is used as cloud based system. We are not going to face limited storage problem.

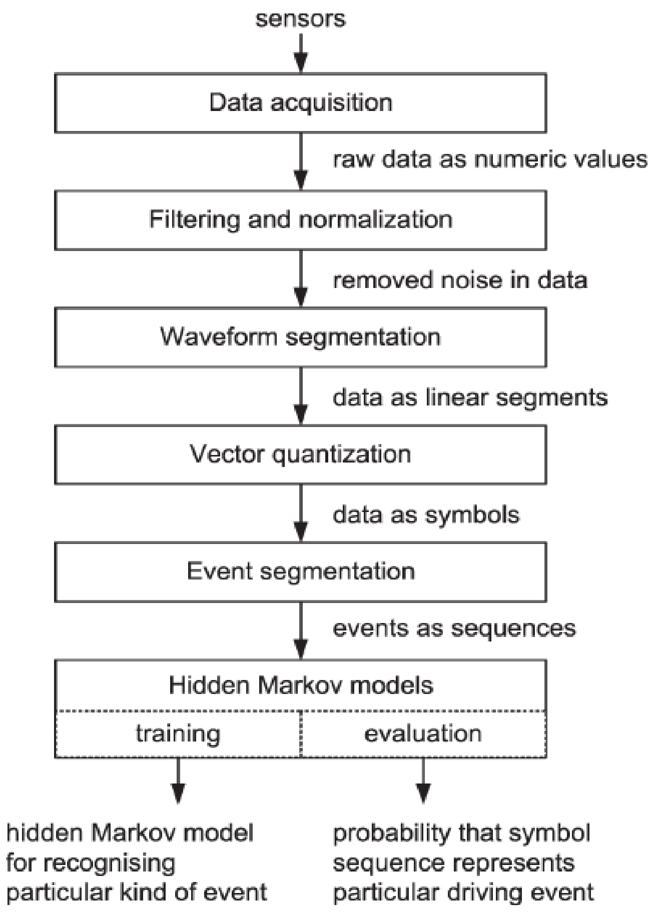


Figure 2.8: Process flow diagram [12].

2.1.10. Driver Behavior Recognition Based on a Driver Model Framework

A driver behavior recognition method based on a driver model framework is presented in [13]. Authors characterized and detect driving pattern and make the framework of a cognitive model of human behavior [5]. HMM-based steering behavior models for emergency and normal lane changes as well as for lane keeping were developed using a moving base driving simulator. Authors did not represent specific driver behaviors classification like Neutral, Assertive, and Aggressive. In this research construct drive behaviors model using drive behaviors recognition methods. This model explains and reproduces drivers' behavioral characteristics. In this study mainly focused on lane change maneuvers among various driving actions. Previously developed some method estimate a driver's lane change intention, but these models data get from vehicle, so this method based on vehicle.

Here they are used driver behavior recognition method based on Hidden Markov Model (HMM). Authors used three different maneuvers to recognize driver behavior. They are emergency lane change, normal lane change, and lane keeping. They used motion based driving simulator to measure driving behavior data and they measure steering angle as data for driver behavior recognition method. This simulation did on a motorway traffic environment was used to measure driver behavior data.

They measured data categorized to three categories. They are emergency lane change, normal lane change, and lane keeping. Three types of lane change event data were extracted according to the period and the first peak of the steering angle. For another category, data were extracted for a five-second interval from the original data measured with the driving simulator.

2.2. Unsafe Driving Behaviors

Real-time abnormal driving behaviors monitoring is very important to improve driving safety. There are so many abnormal driving behaviors and Chen et al. has discussed about six types of abnormal driving behaviors [14]. They are,

a. Weaving - Driving alternately toward one side of the lane and then the other, i.e. serpentine driving or driving in S- shape.

b. Swerving - making an abrupt redirection when driving along a generally straight course.

c. Side-slipping - when driving in a generally straight line, but deviating from the normal driving direction.

d. Turning with a wide radius - Turning cross an intersection at such an extremely high speed that the car would drive along a curve with a big radius, and the vehicle sometimes appears to drift outside of the lane, or into another line.

e. Sudden Braking - when the driver slams on the brake and the vehicle’s speed falls down sharply in a very short period of time

f. Fast U-turn - a fast turning in U-shape, i.e., turning round (180 degrees) quickly and then driving along the opposite direction.

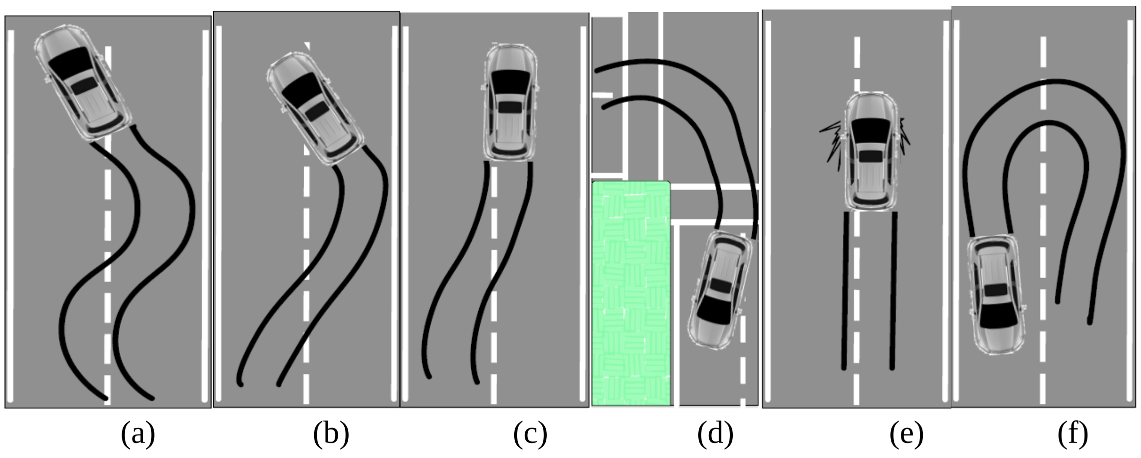


Figure 2.9 : Abnormal Driving Behaviors; (a) Weaving, (b) Swerving, (c) Sideslipping, (d) Turning with a wide radius, (e) Sudden braking, (f) Fast U-turn

All these driving behaviors have an unique pattern on acceleration. When considering weaving pattern, it has a drastic fluctuation on acceleration on x-axis and this fluctuation continues for a period of time. But acceleration on y-axis keeps smooth. Both standard deviation and the range of acceleration on x-axis are very large and time duration is long. The mean value of acceleration on x-axis is around zero. Since swerving is an abrupt, instant behavior, the time duration is very short. When swerving occurs, there is a great peak on acceleration on x-axis. Thus, the range and standard deviation of acceleration on x-axis are large, and the mean value is not near zero. In addition, acceleration on y axis is flat during swerving. When sideslipping occurs, acceleration on y-axis falls down sharply. Thus, the minimum value and mean value of acceleration on y-axis are negative, and the range of acceleration on y-axis is large. In addition, acceleration on x-axis in sideslipping is not near zero. If the vehicle slips toward the right side, acceleration on x-axis would be around a positive value, while if left, then negative. The mean value of acceleration on x-axis thus is not near zero. Since sideslipping is an abrupt driving behavior, the time duration is short. When a driver turns right or left fast in U-shape, acceleration on x-axis rises quickly to a very high value or drops fast to a very low value, respectively. Moreover, the value would last for a period of time. The standard deviation of acceleration on x-axis thus is large on the beginning and ending of a fast U-turn, the mean value of acceleration on x-axis is far from zero and the range of acceleration on x-axis is large. When it comes to acceleration on y-axis, there are no obvious changes. It may take a period of time to finish a fast U-turn; hence, the time duration is long. When turning at an extremely high speed, acceleration on x-axis sees a high magnitude for a period of time, while the acceleration on y-axis is around zero. Thus, the mean value of acceleration on x-axis is far from zero and the standard deviation is large. It may take a period of time to finish a turning with a wide radius, so the time duration is long. When a vehicle brakes suddenly, acceleration on x-axis remains flat while acceleration on y-axis sharply downs and keeps negative for some time. Thus, the standard deviation and value range of acceleration on x-axis are small. On acceleration on y-axis, the standard deviation is large at the beginning and ending of a sudden braking and the range of accy is acceleration on y-axis. Since sudden braking is an abrupt driving behavior, the time duration is short.

Likewise, each of these abnormal driving behaviors have an unique pattern on acceleration on x-axis and y-axis. By analyzing the acceleration data in a certain time period, there abnormal driving pattern can be detected

2.3. OBDII

To collect the driving data, smartphone or OBDII system can be used. But when we consider the accuracy of the data coming from the smartphone and the OBDII system, accuracy of the data collecting from the OBDII is higher than the data collecting from the smartphone. So we used OBDII system to collect vehicular data.

OBDII is a computer-based system that is designed to reduce emissions by monitoring the performance of major engine components. OBD implementations use a standardized digital communications port to provide real-time data in addition to a standardized series of diagnostic trouble codes, or DTCs, which allow one to rapidly identify and remedy malfunctions within the vehicle. OBD system monitors different parameters of vehicle and store information in memory but does not have any interface for users. Whenever a fault arises in the vehicle, the system senses that fault and notifies it to the user using a Malfunction Indicator Light (MIL). This is not an effective way of warning indication because the user cannot tell which part has the fault, what the fault is and when it occurs [15].

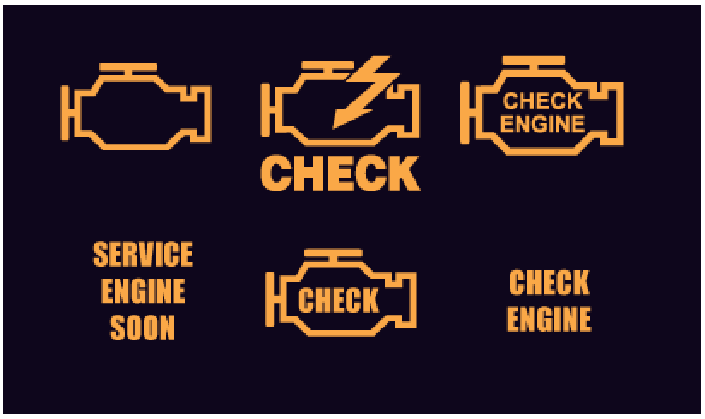


Figure 2.10: Malfunction indicator light / Check engine light.

2.3.1. OBD-II Modes

OBD has defined 10 modes of diagnostics. These modes do not depend on the protocol that is used. Not each mode is necessarily supported by the Engine Control Unit (ECU). Each mode supports for different Parameter Identifications (PIDs) that are used to obtain the vehicular data.

2.3.2. OBD-II signaling protocols

There are five signaling protocols that are permitted with the OBD-II interface. Most vehicles support for only one of the protocols. Those protocols are,

1. SAE J1850 PWM (Pulse with Modulation)
2. SAE J1850 VPW (Variable Pulse Width)
3. ISO 9141-2
4. ISO 14230 KWP2000 (Keyword Protocol 2000)
5. ISO 15765 CAN

Generally, the protocol that is used for the vehicle can be determined by looking at the pinout of the OBD-II connector.

2.3.3. How to access the OBD-II system

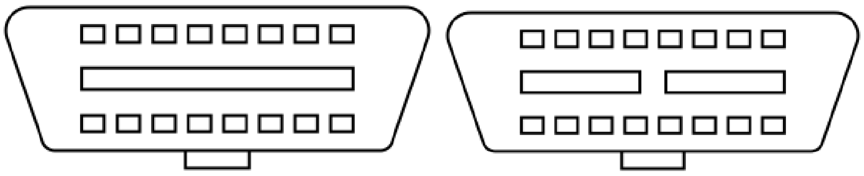
The system can be accessed through the Data Link Connector (DLC). This connector has 16 pins and it can tell us which protocol the car communicates with, depending on which pins are populated in it. Officially this connector is called as an SAE J1962 Diagnostic Connector. This is located at the bottom of the dashboard.

OBD-II Diagnostic Connector/ Data Link Connector (DLC)

There are two types of connectors called Type A and Type B. Both are female, 16-pin, D-shape connectors.

- Type A connector – This is used for vehicles that use 12V supply voltage

- Type B connector – This is used for 24V vehicles.



(a) (b)

Figure 2.11: DLC connector; (a) Type A connector and (b) Type B connector.

In the DLC connector, 9 pins have fixed functions and rest pins have been left to the discretion of the vehicle manufacturer. To communicate with the OBD system, various diagnostic tools can be used. These tools can be connected to the DLC and can be used to retrieve Diagnostic Trouble Codes that is generated by OBD-II system, to display the OBD-II vehicle data.

2.3.5. Diagnostic Trouble Code (DTC)

This code is used to describe what/where and when the failure occurred. OBD system stores this code in the memory inside the Engine Control Unit (ECU). This code can either be generic or unique to vehicle manufacture.

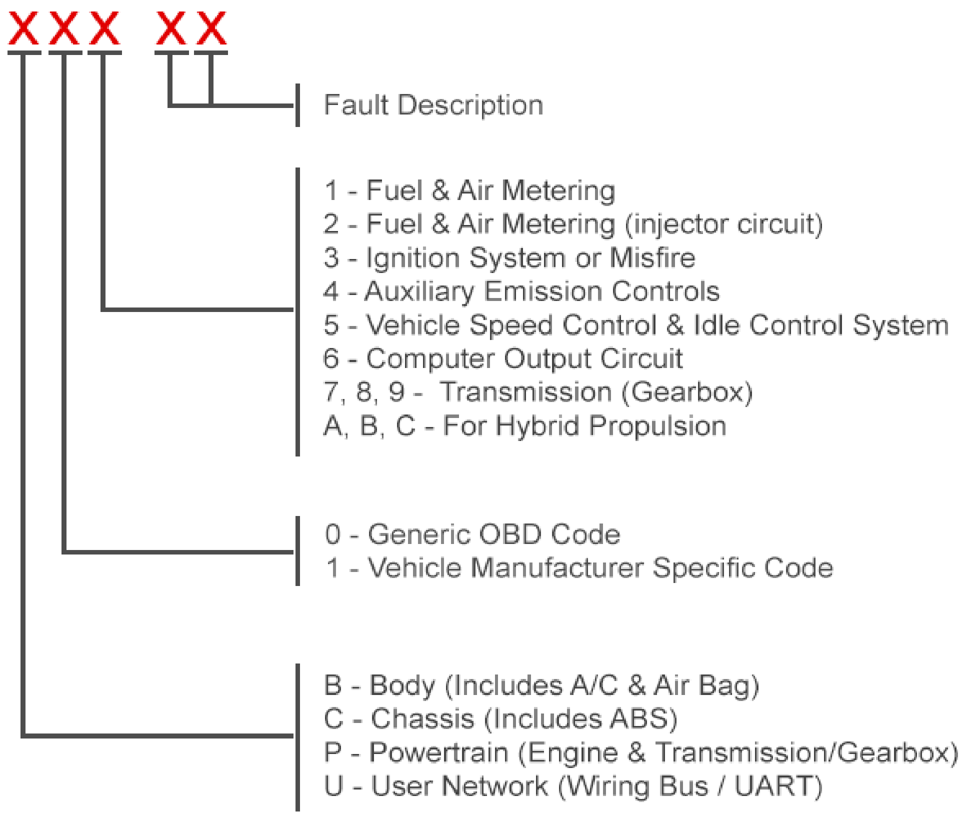

XXX XX
Fault Description
1 - Fuel & Air Metering
2 - Fuel & Air Metering (injector circuit)
3 - Ignition System or Misfire
4 - Auxiliary Emission Controls
5 - Vehicle Speed Control & Idle Control System
6 - Computer Output Circuit
7, 8, 9 - Transmission (Gearbox)
A, B, C - For Hybrid Propulsion
0 - Generic OBD Code
1 - Vehicle Manufacturer Specific Code
B - Body (Includes A/C & Air Bag)
C - Chassis (Includes ABS)
P - Powertrain (Engine & Transmission/Gearbox)
U - User Network (Wiring Bus / UART)

Figure 2.12 :Diagnostic Trouble Code (DTC).

2.3.6.Control Panel of OBD-II Signal Generator

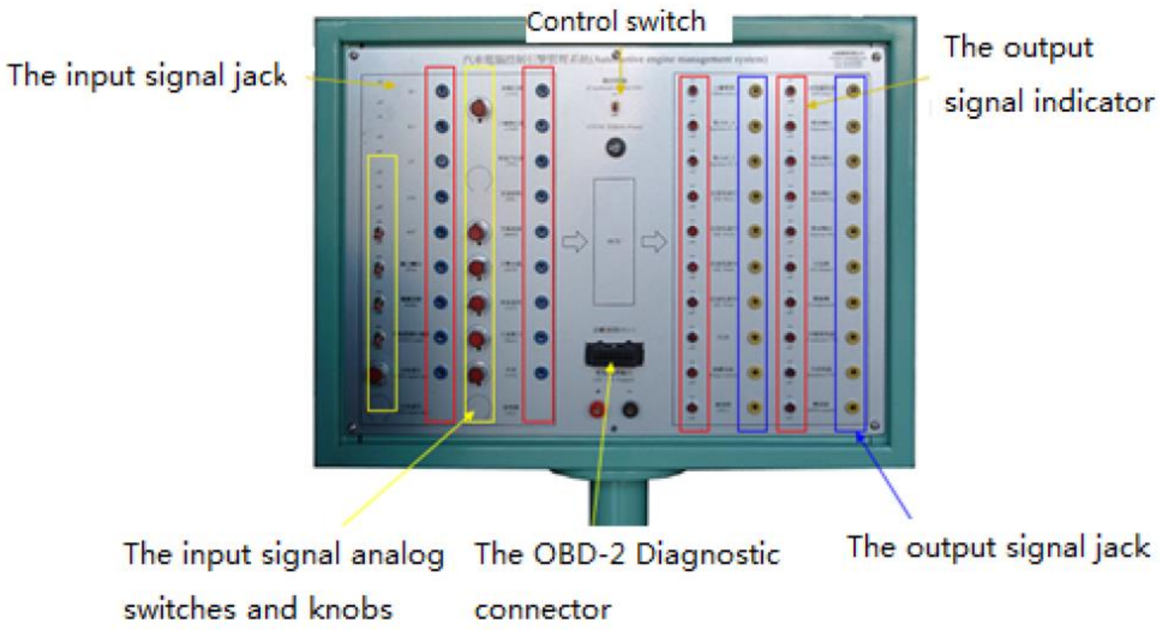

Control switch
The input signal jack
The output signal indicator
The input signal analog switches and knobs
The OBD-2 Diagnostic connector
The output signal jack

Figure 2.13: Control panel of OBDII [5].

The left side of the control panel is OBD data input control terminal and the right side is output control terminal. Middle of the control panel contains interlocking switches and OBD-II data link connector.

- Input control terminal - This has knob input and jack input method. The knob input is manual adjustment mode. The jack input is external analog signal input.
- Output control terminal - This has indicator lights and jack output method. Indicator lights show the operation status of engine components. The jack output can achieve data output displayed on other devices.
- Middle of the control panel - Interlocking switches that are located in the middle of the control panel are designed to control the synchronization between the throttle value and the engine RPM.

When it is in the,

Open state - Acceleration pedal is available to control the throttle and engine RPM at the same time
Close state - One can control throttle and engine RPM individually.

Data link connector achieves the OBD data output.

2.3.7. Decoding OBD Signals

OBD-II provides access to data from the Engine Control Unit (ECU) and provides the valuable information when troubleshooting problems occur inside a vehicle. Here the OBD signal can be decoded via OBD Mode operation with appropriate Parameter Identifications (PIDs) which are defined in J1979. These PIDs are used to request data from a vehicle. That means each PID describes the meaningful vehicle data.

Not all PIDs are supported on all protocols. There are unique, custom PIDs for each manufacturer. These are not generally published. Hence, it needs to do a lot of hunting or reverse engineering to determine to which system each PID relates.

An automotive technician uses PIDs with a scan tool which is connected to the OBD-II connector.

- The technician enters the PID.
- The scan tool sends it to the vehicle's controller-are network (CAN)-bus, VPW, PWM, ISO, KWP.
- A device on the bus recognizes the PID as one it is responsible for, and reports the value for that PID to the bus.
- The scan tool reads the response and displays it to the technician.

2.4. WSO2 Data Analytic Server (DAS)

DAS is a fully open source solution for aggregating and analyzing data and presenting information about the business activities. It provides real-time, batch, interactive and predictive (via machine learning) analysis of data into one integrated platform.

DAS has a ability to build systems and applications that collect and analyze both real-time and persisted data and communicate the results. The workflow of the DAS consists of three main phases. They are [16]**,**

- Collecting Data
- Analyzing Data
- Communicating Results

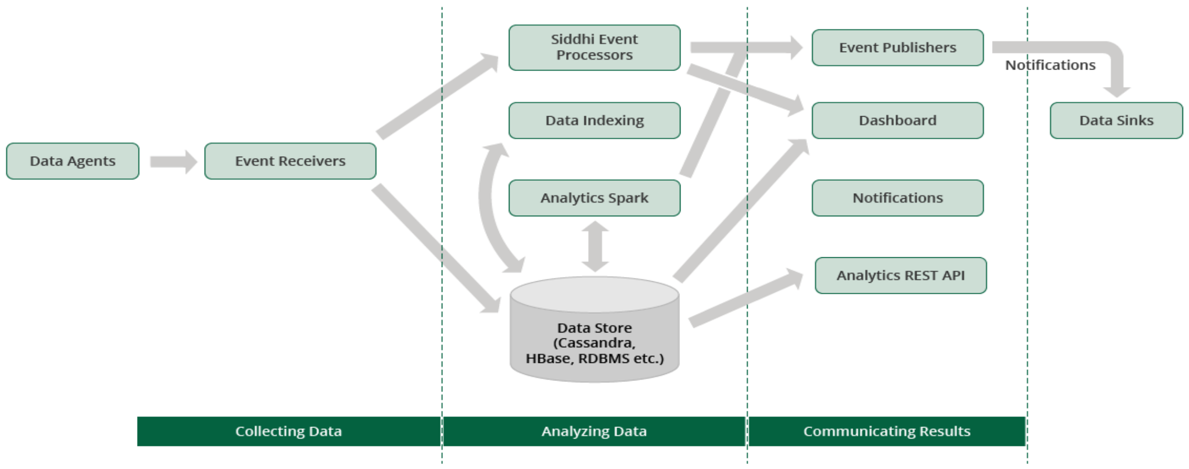


Figure 2.14: DAS architecture [16].

2.4.1 Collecting Data

DAS provides a single API for external data sources to publish data events to it. In addition, it provides configurable options either to process the data event stream inflow for real time analysis, to persist data for batch analysis and to index for interactive analysis.

- Data Agents - Data Agents are external sources which publishes data to DAS. Agent components reside in external systems and pushes data as events to the DAS.
- Event Receivers - Data published by the data agents are received by the event receiver and each event receiver is associated with an event stream which data are persisted or process using Event Processors.

2.4.2. Analyzing Data

DAS provides facilities for real time analysis as well as batch analysis as follows:

- Batch Analysis - Batch analysis can be performed for persist event streams. DAS batch analytics engine is powered by Apache Spark which accesses the underlying data storage and executes programs to process the event data. Spark SQL is used to create analysis plan to be executed
- Real-time analytics - In the DAS, there is a real time analytics engine called as Siddhi Event Processor. This real time analytic engine can process multiple event streams in real-time. All the analysis rules are implemented in an execution plan using Siddhi Query Language. Execution plan is the editor for the event processing logic. An execution plan consists of a set of queries and import and export streams. When an new event occurs this execution plan is executed in the real time analytics engine and produces an output event.
- Interactive analytics - This is used to get fast result through adhoc querying of a data set. Interactive analytics in DAS is possible when selecting to index event stream attributes.
- Predictive Analytics - Predictive analytics for data in DAS is integrated with WSO2 ML.

This integration allows WSO2 ML to use an Analytics table in DAS as a dataset and make predictions/recommendations using that data by applying Machine Learning algorithms.

2.4.3. Communicating results

WSO2 DAS uses several presentation mechanism to present the event notifications and processing results.

- Event Publishers - Output data either from Spark script or Siddhi CEP engine are published from DAS using event publishers.
- Analytic Dashboard - Analytic Dashboard has been created for visualization of analytic data. Dashboard creation is wizard driven, where widgets/gadgets such as line, bar, and arc charts can be used to get data from analytical tables and add them on a structured grid layout to provide an overall view
- Analytics REST API - DAS facilitates REST API based data publishing and REST API can be used with Web applications and Web services.

3. Design

Figure 3.1 illustrates an overview of the proposed system, which consists of five parts as follows:

- Mobile App
- REST API
- Driver Profiling Platform
  - Real-time analysis
  - Batch analysis
- Dashboard
- Database

The mobile app works as a data collector. It collects data from the dongle and sends them to the Driver Profiling Platform (DPP) through a REST API. DPP implements all real time and historical data analysis techniques. Results of the real time and historical analysis are then displayed on the dashboard, as well as send to the mobile app in the suitable form of a feedback to the driver. High-level architecture of the proposed system is illustrated in Figure 3.2. Next, we discuss each of the layers in detail.

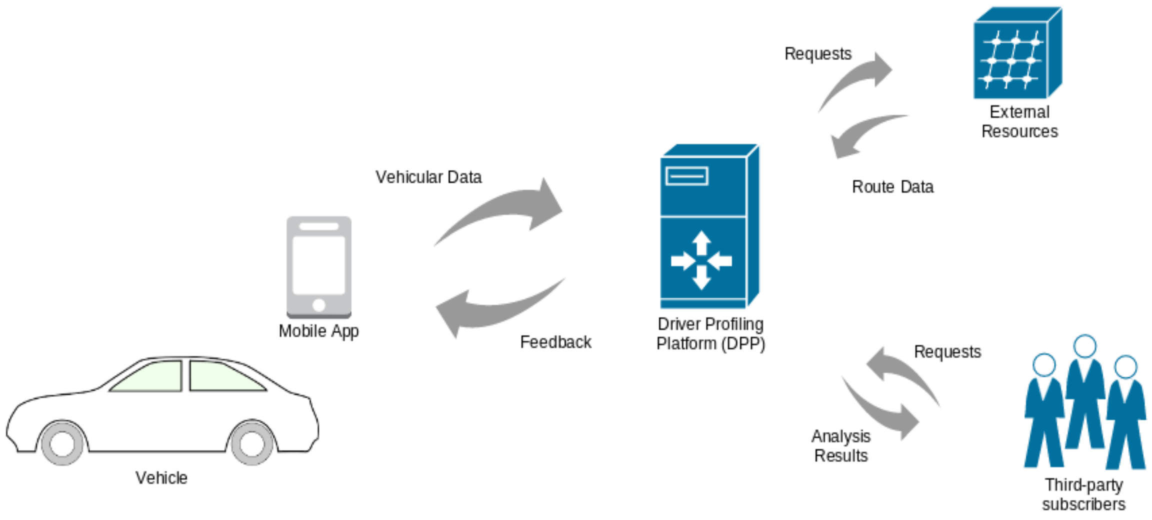


Figure 3.1: Overview of the proposed system.

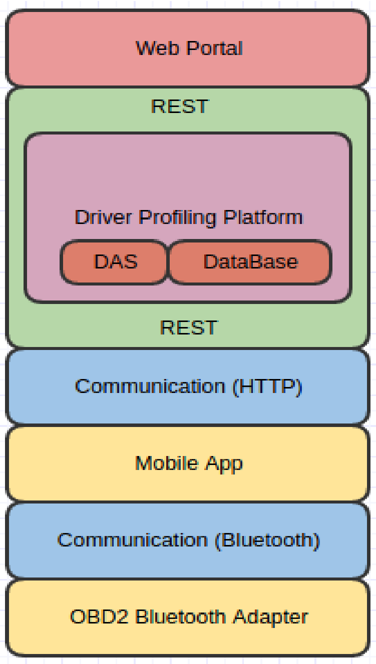


Figure 3.2: High-level Architecture of the proposed system.

3.1. Mobile Application

The mobile application provides three main requirements of the system, namely:

1. Retrieve vehicular data from the dongle via bluetooth.
2. Send data to the server.
3. Generate alerts to the driver on his/her abnormal behaviors.

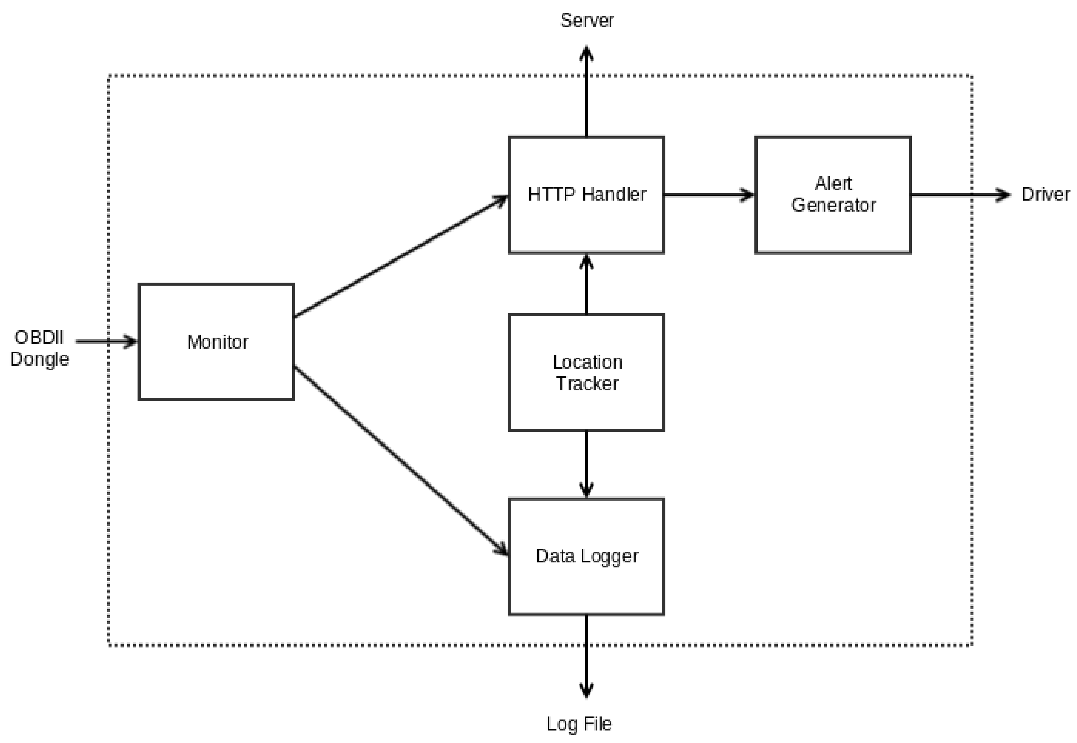


Figure 3.3: High-level architecture of the mobile application.

As seen on Figure 3.3 app consists of five modules, and their functionalities are described in Table 3.1.

Table 3.1: Description of app modules.

Module	**Description**	**Tasks**	**I/O**
Monitor	Stream that is received from OBDII dongle is processed and payloads is generated based on the given configuration.	1. Retrieve specified data from data stream as defined by application. 2. Run simple queries and filter out important records.	Input: OBDII Data stream Output: Predefined data (as a series of events)
Http Handler	Responsible for communication between server and app using HTTP.	1. Maintain connection between application and the server. 2. Send data to server. 3. Retrieve alerts from server.	Input: Payloads and URL to be sent Output: Payloads received from server
Location Tracker	Once the user grants access to GPS on smartphone, module requests location data from smartphone and update the location variable.	1. Maintain current location coordinates. 2. Send coordinates when requested by other modules.	Input: GPS data (from mobile sensor) Output: Longitude and latitude at requested time
Data Logger	All the payloads that is received from the dongle is logged as a CSV (Comma-Separated Values) file in smartphone's internal storage.	1. Writer data records to the log file.	Input: Data records (as payloads) Output: Output stream to be written to a log file.
Alert Generator	When current category of the driver is changed into an abnormal category, an alert is generated to notify driver.	1. Generate alerts to driver on change of category.	Input: Alert information (Type, Title, etc.) Output: Android Alert

3.2. Driver Profiling Platform

In this system the main component is Driver Profiling Platform (DPP). Following three clients communicates with the DDP using a REST API

1. Mobile application
2. Dashboard
3. Third-party users

Figure 3.4 shows the high-level architectural diagram of the DPP. DPP includes three components, namely RESTful API, backend database, and data analytics server. Routing engine, mobile app, dashboard, and third-party client API are connected as external components. DPP provides a RESTful API (REST API) which exposes DPP's functionalities to the clients to get analytic detail, ingest vehicular data, persist data in backend database, and manage user authentication.

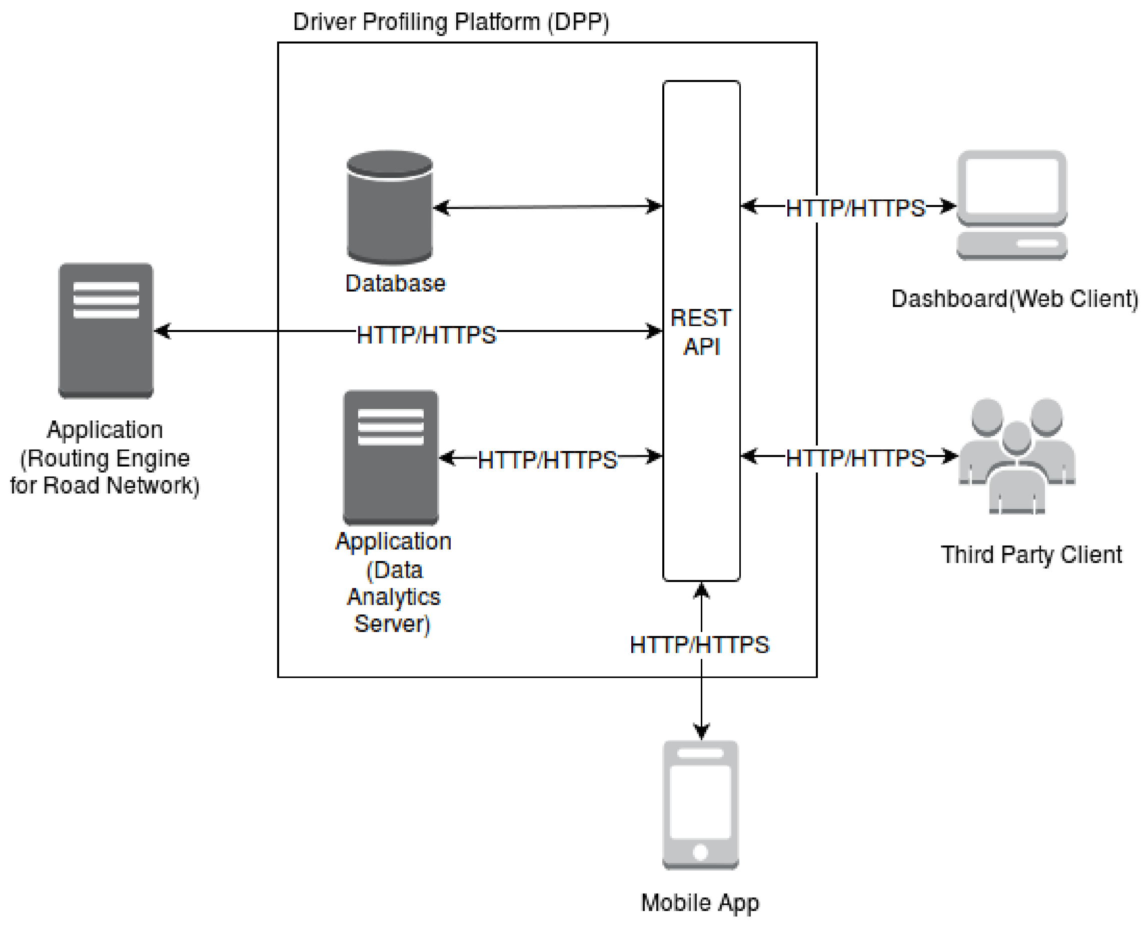


Figure 3.4: High-level architecture of Driver Profiling Platform.

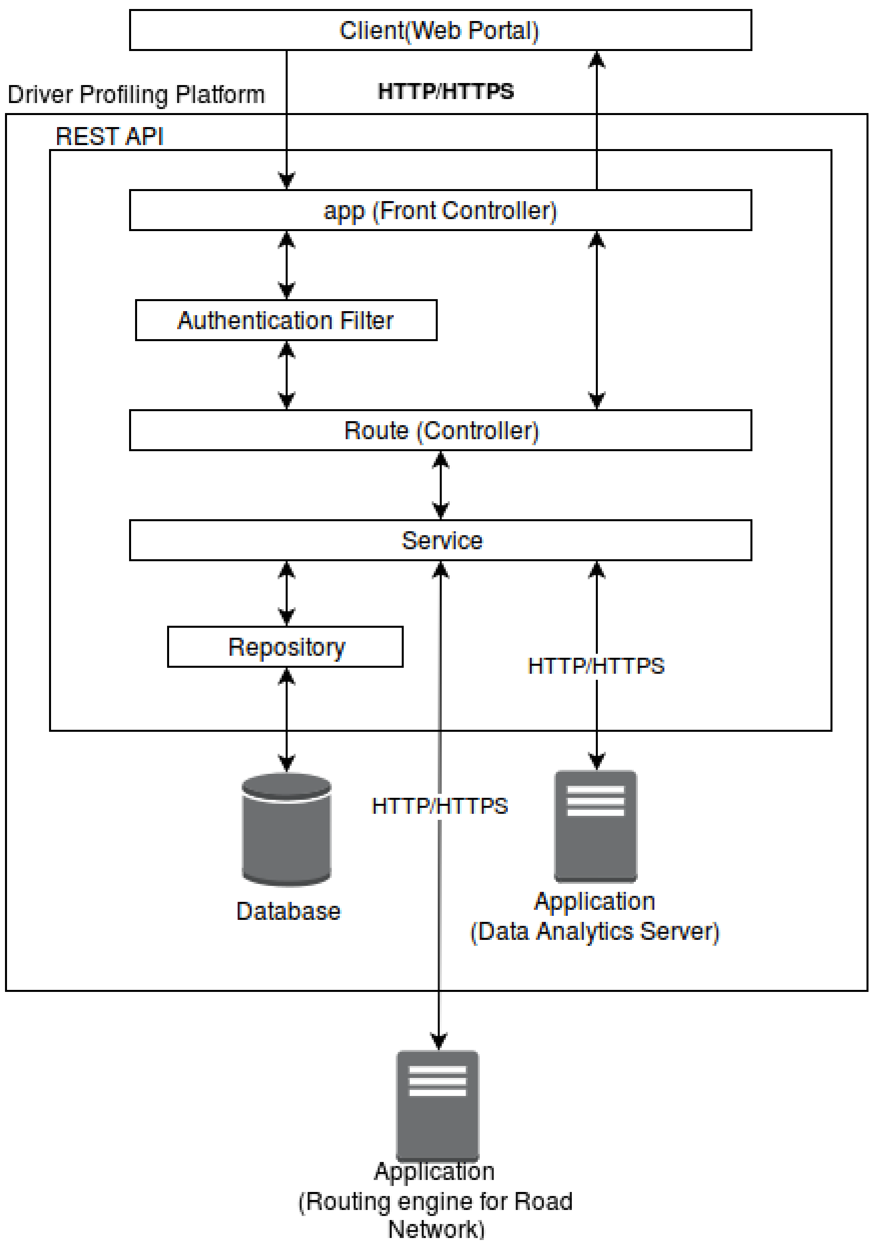


Figure 3.5: REST API architecture diagram.

Figure 3.5 shows the architectural diagram of the REST API. It illustrates how a client's HTTP request executes via REST API. A client (Web portal) sends request (HTTP/HTTPS) to the REST API and the app (Front Controller) which is inside the REST API receives all of those requests and sends them either to the Authentication Filter or Route (Controller). If the client calls a user login request or a user registration (Sign up) request, then app redirects request to the Route (Controller) otherwise app redirects request to the Authentication Filter. Authentication filter checks whether the user is valid or not and if it is, sends the filtered URL to the Route (Controller). If the user is not valid, authentication filter sends a response to the client informing that the user authentication is invalid. When the request reaches to the controller, the controller calls for the services according to the client's request and then services access the database via repository (Data Access Object) and the application via HTTP/HTTPS requests according to the need of the client. These applications are web servers which provide following services related to the system:

1. Data Analytic Server (DAS) - This service is with DPP and analyzes o driving data. In this scenario REST services publish vehicular data as driving data which are published by mobile app in the REST services and request result of driving behavior analysis according to the client request.
2. Routing Engine for Road Network - This is a third-party application outside the DPP. Routing engine use to get route information according GPS data(*longitude, latitude*) in vehicular data. The routing engine provides diffrence services to get road network information. When the DPP REST services call only trip services to get information about trip using GPS data. Using this service the DPP get trip distance and route type like road network information.

Next, we discuss services supported by the DPP REST API.

3.2.1. Authentication

DPP uses a shared-key authentication mechanism to maintain under the authorization of DPP. As seen in Figure 3.6, client applications send login request to the REST API before calling the other services of the REST API. If the login request is successful, then REST API sends shared key to the client as response to the login request. Client must attach this shared key with all future API calls after the login request. Because client calls all request exclude login, signup and data analytics server publisher request go through authentication filter. When this filter checks whether the shared key attaches with a request is valid or not. If the shared key is valid, then request is forwarded to the route to access service. Otherwise, forwards request to the app indicating authentication failed response.

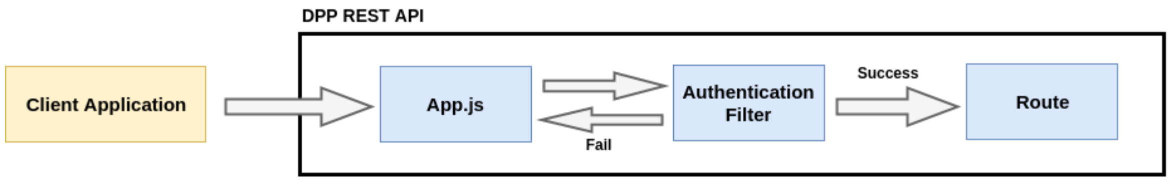


Figure 3.6: Authentication service flow diagram.

3.2.2. Vehicular Data Publisher

Vehicular data publisher service forwards vehicular data which are sent by mobile app into data analytics server's input stream (see Figure 3.7). When mobile app publish data via the REST API, then the API generates and attaches trip ID and vehicle registration number to the payload of vehicular data and forward (i.e., publish) modified payload in the DAS input stream.

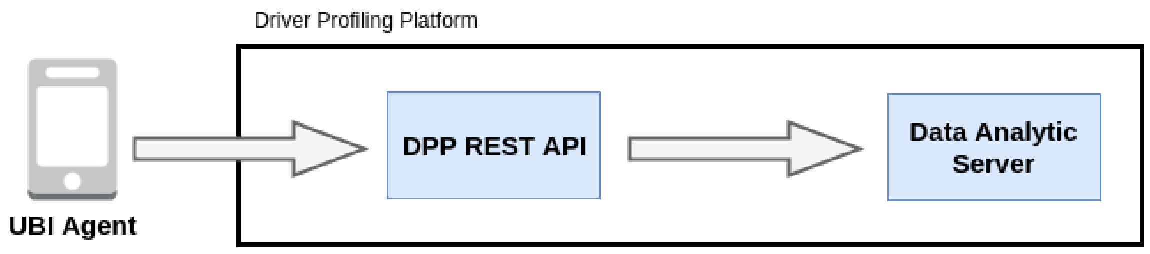


Figure 3.7: Vehicular data publisher service flow diagram.

3.2.3. Driving Behavior Analysis Results

Driving behavior analysis service produces both historical and real time analysis results. As seen in Figure 3.8 analysis data are directly retrieved from DAS according to the client application request. When the client application requests historical driving behavior data through the REST API, it is routed to the DAS. After retrieving historical analysis data from DAS, response is send back to the relevant client. A response typically consists of following attributes:

- Relative Skill Score value (RSS)
- Relative Aggression Score value (RAS)
- Driver category history
- Current category of all users
- Driving cycle data (e.g., acceleration count details)
- Safety factor
- Comfort factor

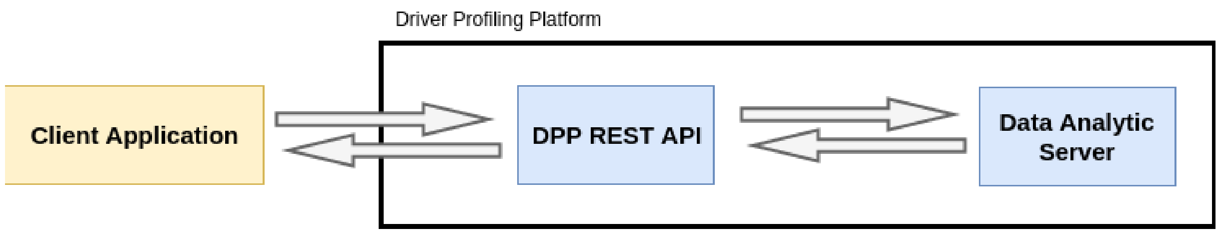


Figure 3.8: Flow diagram for obtaining historical driving behavior analysis results.

Figure 3.9 illustrates the process of retrieving real-time analysis data from the backend database based on the client application request. When client application requests real-time driving behavior data via the REST API, request is routed to the persist data in backend database. The response is then send back to the relevant client.

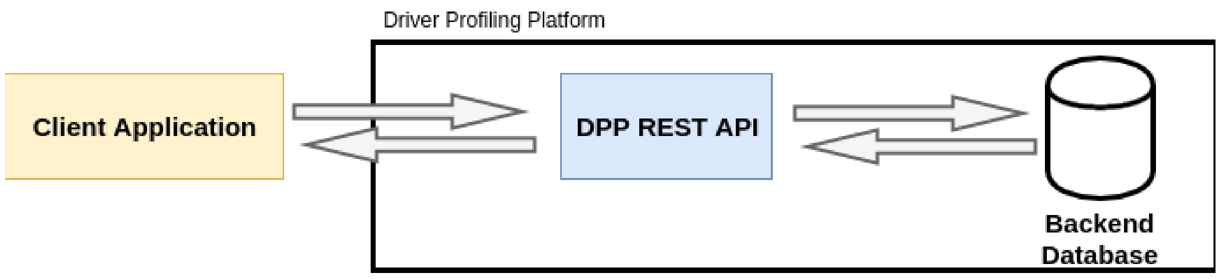


Figure 3.9: Flow diagram for obtaining real-time driving behavior analysis results.

3.2.4. DAS Stream Publisher

When real-time driving behaviors trigger at event in the DAS, then DAS publishes the result via the REST API. As seen in Figure 3.10 these real-time behavior results are published via the REST API of DPP. After publishing the results they are persisted in the backend database.

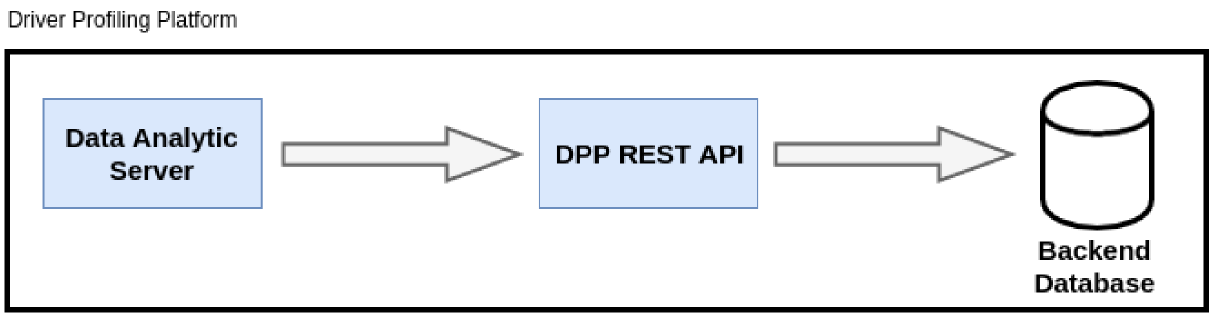


Figure 3.10: DAS publisher service flow diagram.

3.2.5. Profile Summary

As seen on Figure 3.11 this service provides information about the driver profile including trip summary. Profile summary service relies on three services listed in Table 3.2 to retrieve this information. Profile summary service in the REST API mainly focuses on third-party client (such as UBI agents) of DPP. They can use this service to get summary of drivers (clients).

Table 3.2: Description of profile summary service retrieves information.

Component	**Services**	**Retrieve Information**
Data Analytics Server (DAS)	Summary of historical driving behavior analysis results	Current category of user, Safety factor, User driving behavior scores.

Routing engine	Trip detail (using GPS points (*longitude, latitude*) detail)	Distance, Route type
Backend database	Summary of real-time driving behavior Analysis results	Hard acceleration, hard deceleration, weaving, and slide slipping count

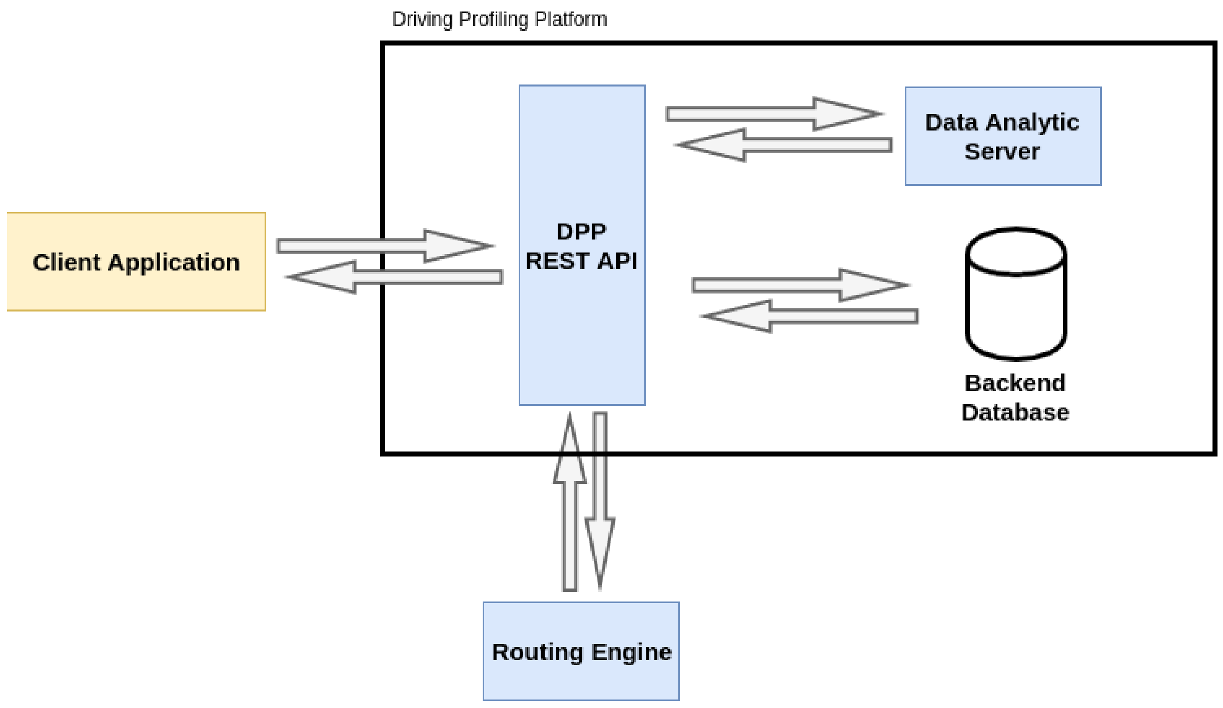


Figure 3.11: Profile summary service flow diagram.

3.3. Real-Time Analytics

The main objective of real-time driving data analysis is to evaluate a driver's real-time behavior detects abnormal driving behaviors, and then make drivers aware about those behaviors. Following attributes are calculated to detect driver behavior and then shown on the dashboard:

- Average speed
- Acceleration
- Hard acceleration count
- Hard deceleration count

On the dashboard, average speed variation and acceleration variation are displayed as time series graphs. Hard acceleration and deceleration counts are displayed as numbers over a given period of time.

The system can detect five types of abnormal driving behaviors. They are weaving, swerving, sideslipping, turn with wide radius, and sudden braking [14]. Abnormal driving behaviors have their unique pattern on acceleration. Because of that, acceleration along x and y axis and time can be used to detect these abnormal driving behaviors. Normal driving behavior is smooth and safe driving with a few fluctuations. In addition, acceleration along and y axis are not very large. Moreover, mean, standard deviation, minimum and maximum values in acceleration along both axis are near zero. Whereas abnormal driving behaviors are risky driving with high fluctuations in mean, standard deviation, minimum, and maximum values along box axis.

Due to these variations on acceleration data, statistics such as average, standard deviation, minimum, maximum and range of acceleration data on x-axis and y-axis are calculated to analyze driving data to detect abnormal driving behaviors. Here threshold values for each of these statistics were defined according to the abnormal driving behaviors and driving data are compared with these pre-defined threshold values to detect abnormal driving patterns. These rules have been implemented on the DAS. DAS has been set up in the DPP in the backend. DAS provides both real time and long-term data analysis facilities with high performance. Because of that, we used DAS to implement these set of rules.

The mobile app sends data as events to the backend through the REST API, which is then forwarded to the DAS (see Figure 3.13). Event receiver is associated with an event stream and it persists incoming data for batch analysis. Moreover, it directs the stream to the Siddhi Complex Event Processor (CEP) inside DAS for real-time processing. All the rules have been implemented on this Siddhi event processor using Siddhi queries. If Siddhi detects abnormal driving behaviors, it is sent to the output stream and output stream directs it to the event publisher. Event publisher publishes those data to the dashboard through the REST API. Dashboard shows those data as a count (number of times each abnormal driving behavior occurs during the corresponding trip). In addition, those data are persisted in output stream for batch analysis. Moreover, average speed, acceleration, and hard acceleration and deceleration data also published to the dashboard by DAS. Figure 3.14 shows the event flow in the DAS**.**

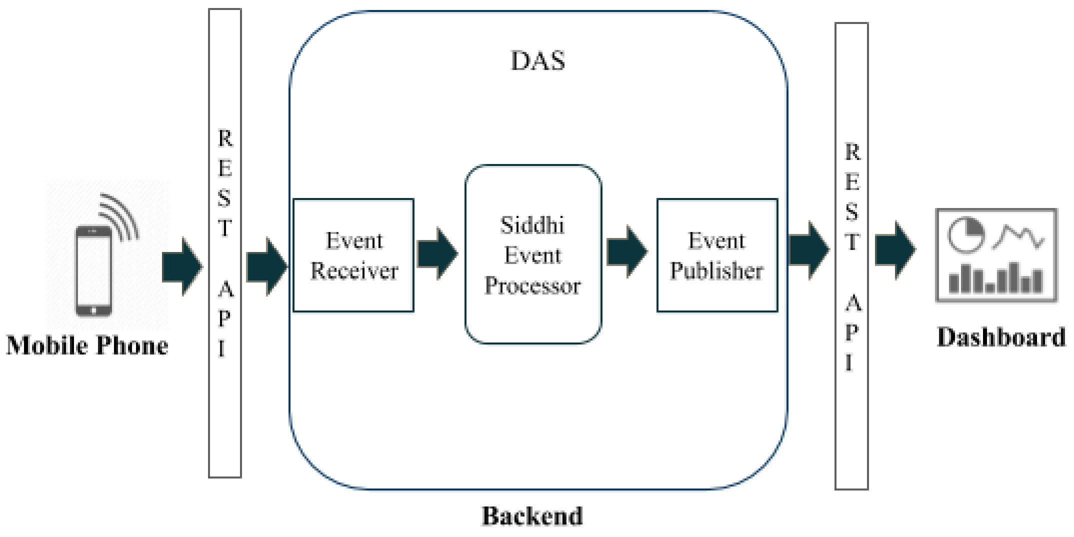


Figure 3.12: Real-time data analysation process.

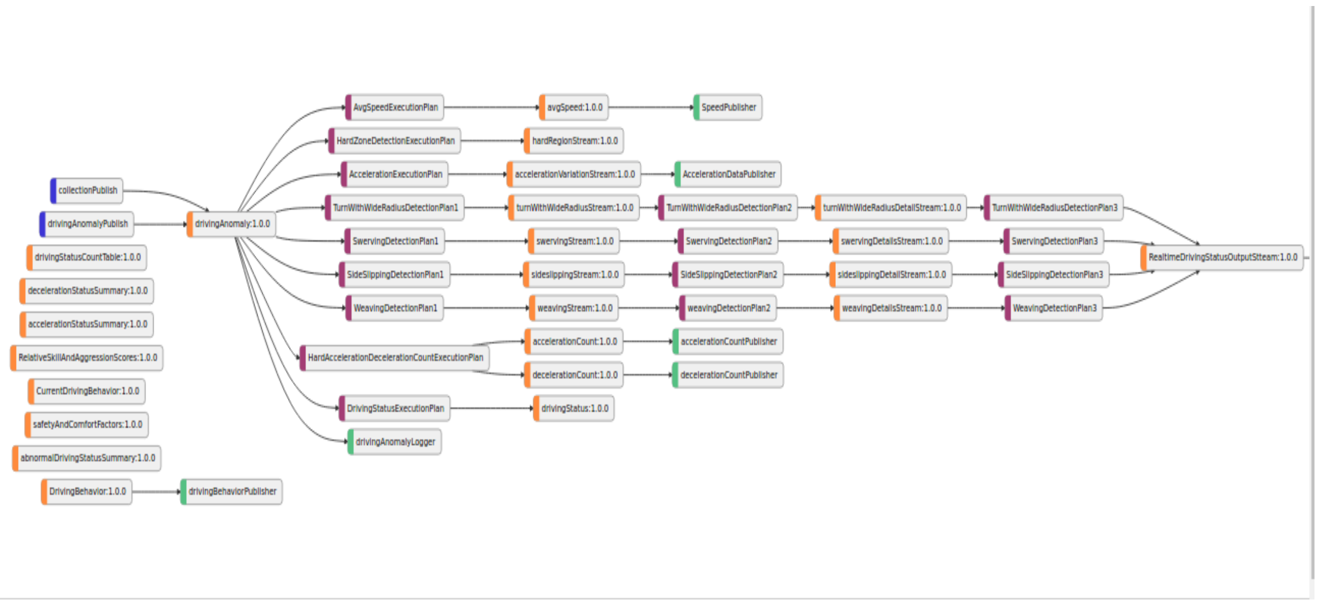

collectionPublish
drivingAnomalyPublish
drivingStatusCountTable:1.0.0
decelerationStatusSummary:1.0.0
accelerationStatusSummary:1.0.0
RelativeSkillAndAggressionScores:1.0.0
CurrentDrivingBehavior:1.0.0
safetyAndComfortFactors:1.0.0
abnormalDrivingStatusSummary:1.0.0
DrivingBehavior:1.0.0
drivingBehaviorPublisher
drivingAnomaly:1.0.0
AvgSpeedExecutionPlan
HardZoneDetectionExecutionPlan
AccelerationExecutionPlan
TurnWithWideRadiusDetectionPlan1
SwervingDetectionPlan1
SideSlippingDetectionPlan1
WeavingDetectionPlan1
HardAccelerationDecelerationCountExecutionPlan
DrivingStatusExecutionPlan
drivingAnomalyLogger
avgSpeed:1.0.0
hardRegionStream:1.0.0
accelerationVariationStream:1.0.0
turnWithWideRadiusStream:1.0.0
swervingStream:1.0.0
sideslippingStream:1.0.0
weavingStream:1.0.0
accelerationCount:1.0.0
decelerationCount:1.0.0
drivingStatus:1.0.0
SpeedPublisher
AccelerationDataPublisher
TurnWithWideRadiusDetectionPlan2
SwervingDetectionPlan2
SideSlippingDetectionPlan2
weavingDetectionPlan2
accelerationCountPublisher
decelerationCountPublisher
turnWithWideRadiusDetailStream:1.0.0
swervingDetailsStream:1.0.0
sideslippingDetailStream:1.0.0
weavingDetailsStream:1.0.0
TurnWithWideRadiusDetectionPlan3
SwervingDetectionPlan3
SideSlippingDetectionPlan3
WeavingDetectionPlan3
RealtimeDrivingStatusOutputStteam:1.0.0

Figure 3.13: Event flow to detect abnormal driving behaviors.

3.4. Historical Analysis

Under historical analysis, we implemented two solutions to estimate driving style, skill, and aggression based on Driving Style Recognition Using Fuzzy Logic [11] and My Drive Behavior Analytics Method and Platform [9]. Based on these techniques drivers are evaluated based on their:

- Skill score
- Aggression Score
- Comfort Score
- Safety Score

These scores can be used for drivers to improve their driving skills as well as for the UBI insurance companies to calculate their insurance premiums. Generally, skill score can be defined as “driver’s unintentional passive characteristics”. For example, change lanes slowly maintaining distance from lead vehicle. Similarly, aggression is defined as “driver’s intentional active characteristics” which can be “attributed to driving style”. For example, overtake slow driver on the inside”. Therefore, these behaviors can be revealed by analyzing the acceleration pattern of the drivers. Because of that, all these scores are calculated based on the aggression profile of all the completed trips.

3.4.1. Driving Score Calculation

Tanushree et al. [9] proposed an algorithm to monitor, quantify, and classify driving style using long-term driving data. Skill score and the aggression score are calculated based on the longitudinal and lateral acceleration of the driving data. Figure 3.14 illustrates the overall process.

Calculating Skill Score and Aggression Score

A set of kurtosis values (normalized fourth order moment about mean) of lateral and longitudinal acceleration from each trip of each drivers are computed. Typically, an experienced or skilled driver is expected to maintain the same driving style for all his trips. Because of that, this idea can be validated through the probability distribution of the kurtosis values. Kurtosis value is an indicator of peakedness and heavy tail of probability distribution. Higher kurtosis means a greater variance is the result of infrequent extreme deviation and the lower variance is frequent modestly sized deviations. Therefore, the probability distribution of the kurtosis values of the skillful drivers tends to follow normal distribution with a few outliers. Kurtosis values are obtained as follows:

$$\boldsymbol{Kurtosis\ value} = n\,\frac{\sum_{i=0}^{n}(x_i - \mu)^4}{\left(\sum_{i=0}^{n}(x_i - \mu)^2\right)^2} \tag{3.1}$$

Next, for each driver, mean (μ) and standard deviation (□) for the set of kurtosis values of longitudinal and lateral accelerations are calculated (Table 3.1 list the set of symbols).

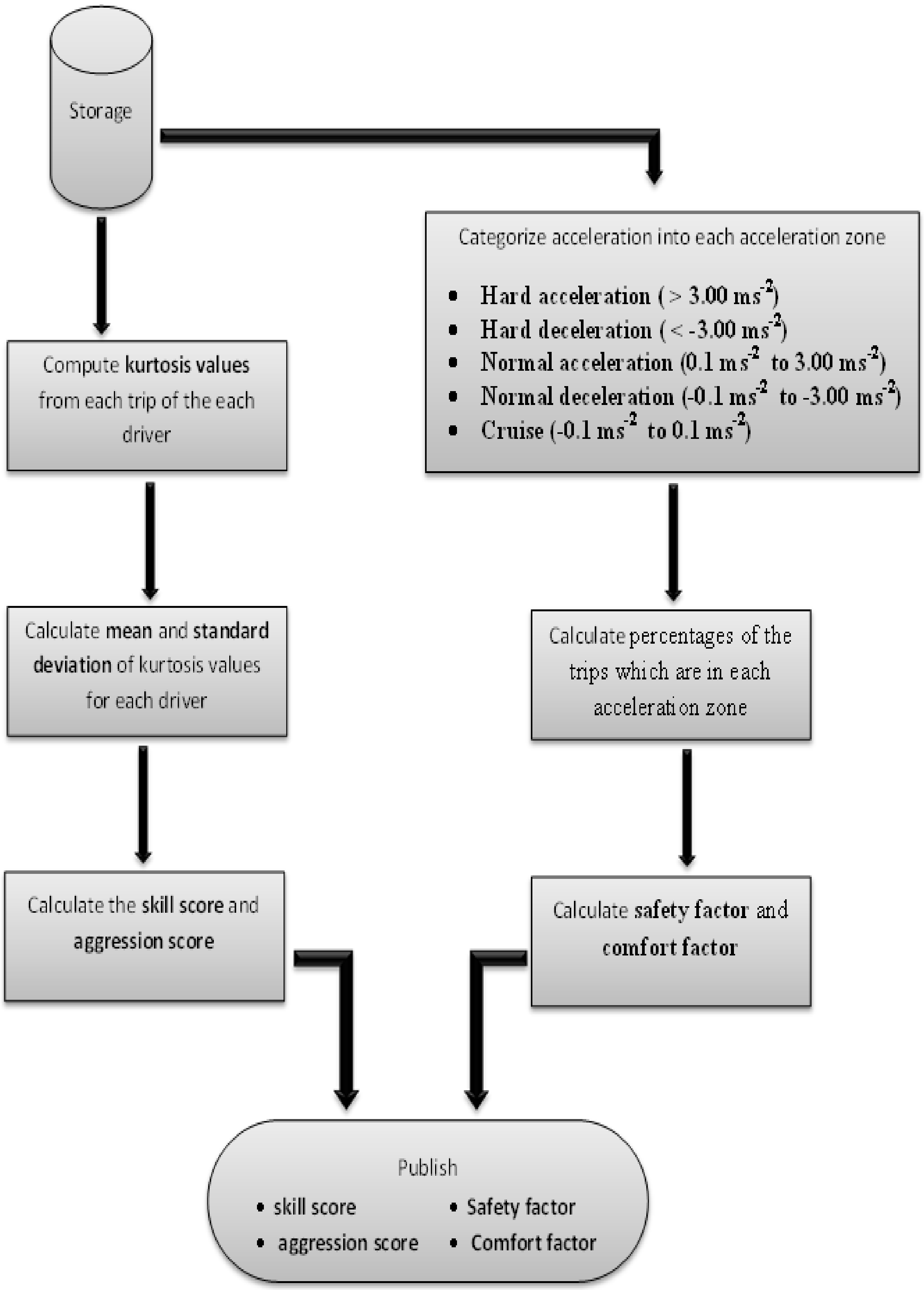

Storage
Compute kurtosis values from each trip of the each driver
Calculate mean and standard deviation of kurtosis values for each driver
Calculate the skill score and aggression score
Categorize acceleration into each acceleration zone
Hard acceleration (> 3.00 ms^{-2})
Hard deceleration (< -3.00 ms^{-2})
Normal acceleration (0.1 ms^{-2} to 3.00 ms^{-2})
Normal deceleration (-0.1 ms^{-2} to -3.00 ms^{-2})
Cruise (-0.1 ms^{-2} to 0.1 ms^{-2})
Calculate percentages of the trips which are in each acceleration zone
Calculate safety factor and comfort factor
Publish
skill score
aggression score
Safety factor
Comfort factor

Figure 3.14: Overall process of driving score calculation.

Then Skill Score Absolute (SSA) and the Aggression Score Absolute (ASA) are calculated for each driver as follows:

$$\textbf{Skill Score Absolute (SSA)} = \frac{1}{\sigma_{log}} + \frac{1}{\sigma_{lat}}$$

$$\textbf{Aggression Score Absolute (ASA)} = \mu_{lag} + \mu_{lat} \qquad (3.2)$$

Table 3.3: Set of symbols.

Symbol	Description
σ_{log}	Standard deviation of the kurtosis values of longitudinal accelerations
σ_{lat}	Standard deviation of the kurtosis values of lateral accelerations
μ_{log}	Mean value of the kurtosis values of longitudinal accelerations
μ_{lat}	Mean value of the kurtosis values of longitudinal accelerations
σ_{LS}	Standard deviation of SSA's of all drivers
σ_{LA}	Standard deviation of ASA's of all drivers
μ_{LS}	Mean value of SSA's of all drivers
μ_{LA}	Mean value of ASA's of all drivers

After calculating absolute scores, relative scores with respect to entire driver group is obtained as follows:

Relative Skill Score (RSS) $= \frac{SSA - \mu_{LS}}{\sigma_{LS}}$

Relative Aggression Score (RAS) $= \frac{ASA - \mu_{LA}}{\sigma_{LA}}$ (3.3)

Higher skill score (RSS) means that the driver is skilled driver and the higher aggressive score (RAS) means the driver is more aggressive. According to these scores, driving styles can be categorized as follows (see Figure 5.4).

● Novice	: low skill score and low aggression score
● Cautious	: high skill score and low aggression score
● Risky	: low skill score and high aggression score
● Rival	: high skill score and high aggression score

Calculating Safety Score and Comfort Score

This algorithm is also based on acceleration data of all the completed trips and the total number of trips of the drivers. First, acceleration data are categorized into following groups based on [9]:

- Hard acceleration (> 3 ms^{-2})
- Hard deceleration (< -3 ms^{-2})
- Normal acceleration (0.1 ms^{-2} to 3 ms^{-2})
- Normal deceleration (-0.1 ms^{-2} to -3 ms^{-2})
- Cruise (-0.1 ms^{-2} to 0.1 ms^{-2})

Here the analysis results are presented as a pi-chart which shows relative percentage of accelerations in normal vs. risky zone. Therefore, percentages of the trips which are in each acceleration zone are calculated to get the safety factor and the comfort factor. Safety factor for each driver is calculated from the percentage of overall trip is in harsh zone (hard acceleration/deceleration). Comfort factor is computed from the percentage of overall trip spent in cruise model.

3.4.2. Driving Style Estimation

For the historical analysis, we also focused on how to recognize the driving events of a particular driver and characterize it as below normal, normaL, abnormal, and very abnormal driving based on the readings of 2-axis accelerometer and speedometer.

Using 2 axis accelerometer and speedometer, we calculate g-force and average speed. As we use 2-axis accelerometer embedded OBD-II dongle, we are directly received longitudinal and lateral accelerations and speed per period of unit time. Then we calculate following "Norm" and "Speed Average" of that particular vehicle according to the request of dashboard.

Norm(n) $= \sqrt{X - acceleration^2 + \, Y - acceleration^2}$ (3.4)

Averaged Norm(i) $= \frac{1}{N}\Sigma$ (3.5)

Averaged Speed = Total Speed / N (3.6)

Where *N* is depend on the time period that is requested from dashboard user. After the calculation of these parameters, we use a fuzzy logic inference system to determine whether the considered driver is risky or not using following membership functions. According to the Figure 3.15, get the related degree of membership value with respect to the calculated Norm value. Then ge the related degree of membership value with respect to the given average speed value Figure 3.16. Based on these two degree values, we get the related category number using the membership function of category Figure 3.17

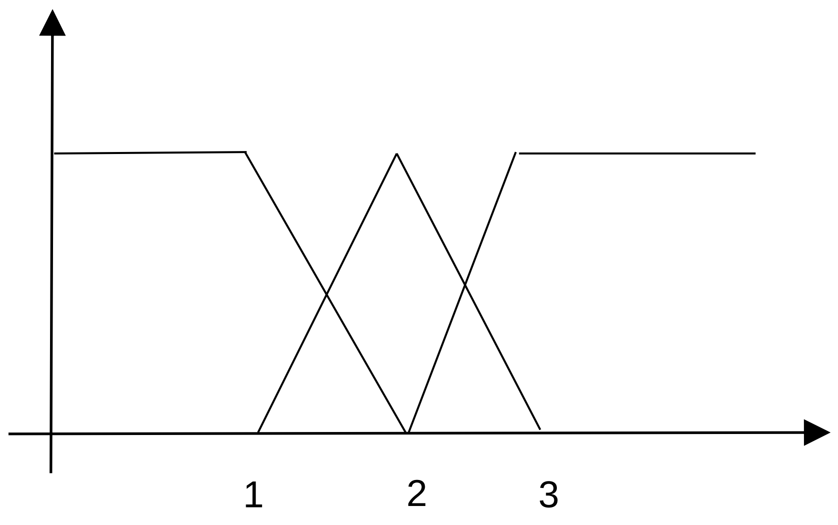


Figure 3.15: Membership function for averaged norm.

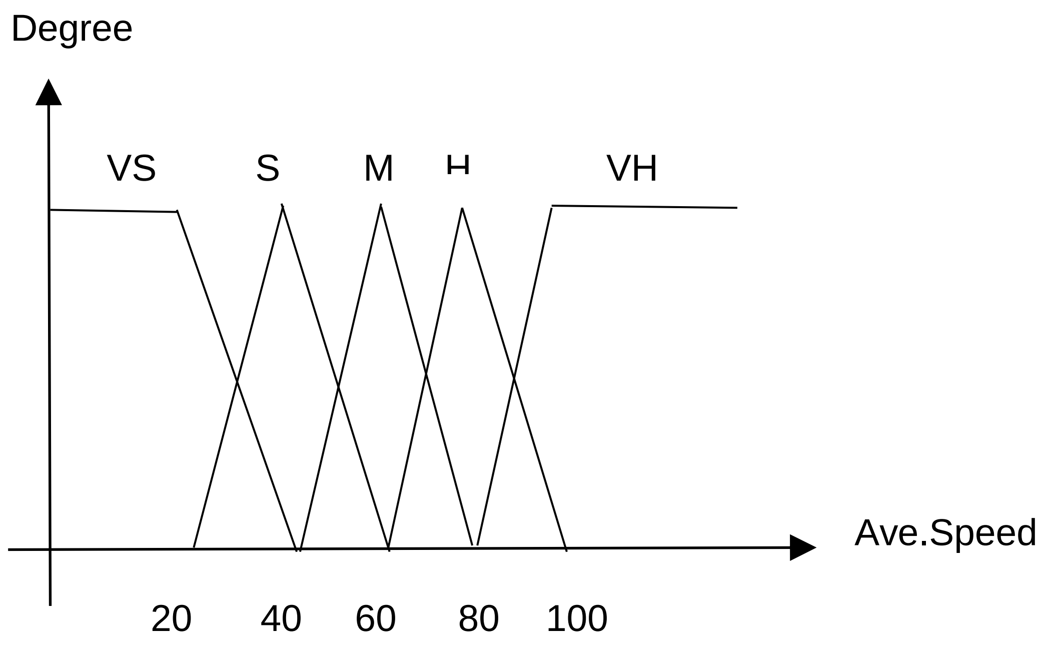


Figure 3.16 Membership function for averaged speed.

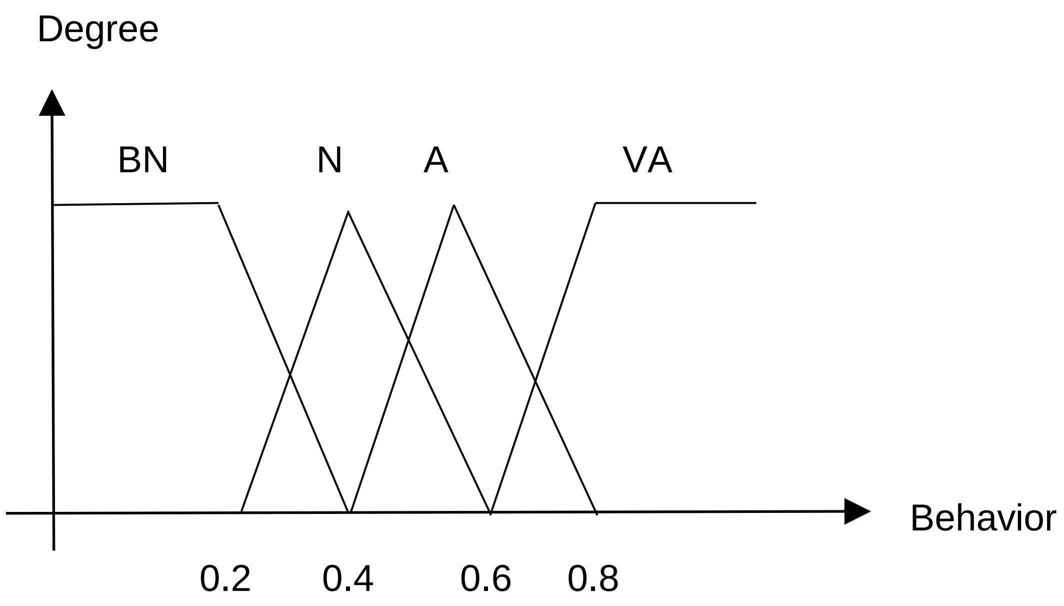


Figure 3.17: Defuzzification function for driving behavior.

4. Implementation

4.1. Languages, Tools, and Technologies

Linux was used as our main development platform. In the system, WSO2 Data Analytic Server (DAS) version 3.1.0 is used to perform real-time and batch analysis tasks. In addition to the DAS, following IDEs and languages were used to continue our rest of project tasks:

- Mobile App

  Languages - Android

  IDE - Android Studio
- REST API

  Language - Node.js

  IDE - Intellij IDEA

  According to the way of calculating trip distance of particular driver, we have to use third party service named Open source Routing Machine (OSRM)
- Real time Analysis

  Languages - Siddhi
- Batch Analysis

  Languages- SPARK, JAVA(UDF)
- Dashboard

  Languages - HTML, JS, AngularJS, Jquery, D3 - V3, D3-V4.

  IDE - Webstorm
- Database

  Languages - NoSQL

  Database Engine - MongoDB

4.2. Mobile Application

The Mobile Application is implemented using Android SDK and the SDK that provided with the selected ODBII dongle. The minimum SDK-version needs to run the app is Android API-level 21. The mobile which runs this app must have a Bluetooth, GPS, and Internet connection to execute the tasks.

4.2.1. Retrieving OBDII data

The SDK of the relevant dongle is responsible to maintain the connectivity with the dongle. The Monitor module in the Android app is subscribed to RPM, speed, x-axis acceleration, and y-axis acceleration data from the SDK of the dongle so that it receives the data as they come from the dongle.

4.2.2. Generating payload

Android provides an object called LocationManager. Using that, the application retrieves current GPS coordinates to the Location Tracker module. The application requests OBDII data from Monitor module and GPS data from Location Tracker module and they are wrapped as a JSON payload and given to the HTTP Handler module.

4.2.3. Transmitting Payload to Central Server

HTTP Handler (see Figure 3.3) is responsible to maintain the connectivity with the REST API of the central server. When a payload is given to the module, it transmits it to the REST API. After each transmits, it waits for the response. If the module receives a status code other than SUCCESS (200), the module will stop sending further payloads and the error code received will be displayed to the user as well.

At the time of initiation, before sending the payloads to the central server, the user has to sign into the server through the application. Once the signing is successful, the server sends a JWT Token to the application which expires after 15 minutes. When sending the payloads, the HTTP Handler include the token in each payloads header to authenticate the user. “java.net*” packages were used to implement this module.

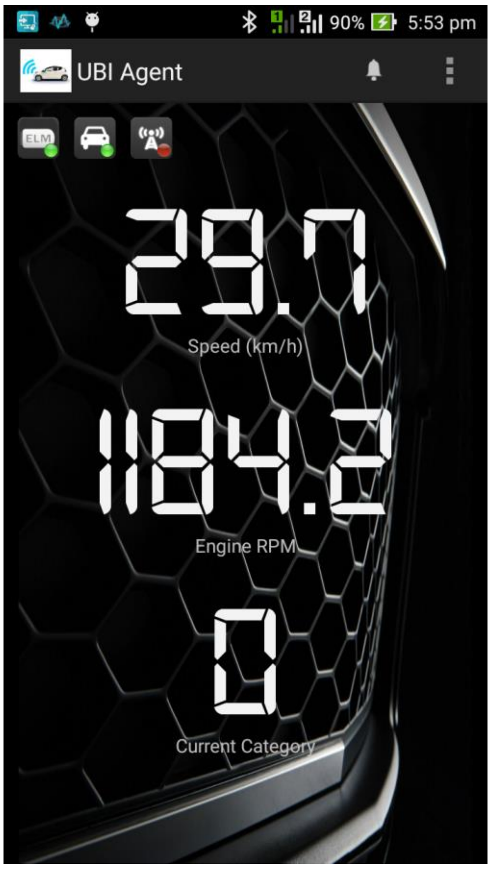


Figure 4.1 : Main screen of the Mobile App.

As seen in Figure 4.1, the app shows real time speed and RPM data which is received from the dongle. The current category is pulled from the backend and shown to the driver based on the category which he belongs to (as very abnormal, abnormal, normal, and below normal).

Three icons on top left indicate app states as described in Table 4.1.

Table 4.1: Indicators on mobile app.

Success	**Fail**	**Meaning**
ELM 🟢	ELM 🔴	Status of connectivity with the dongle.
🚗 🟢	🚗 🔴	Status whether live data is receiving from the dongle or not.
📡 🟢	📡 🔴	Status of connectivity with the REST API of central server.

4.3. REST API

The REST API presented in Section 3.2 is implemented using Node.js and Express web application framework. REST API is called via HTTP and acceed allow methods are PUT, POST, GET, DELETE, and OPTIONS. Payloads are transferred as JSON objects. The REST services communicate with WSO2 DAS, backend database, and Open Source Routing Machine (OSRM) which routes API calls.

DPP implementation supports three type of communication between the REST services and WSO2 DAS. These are,

- WSO2 DAS publish result data to the REST API.
- WSO2 DAS persist result data in their backend database. Then WSO2 DAS expose Analytic data service as REST API access this persist data. DPP services call this Analytic REST API for get these result.
- DPP REST services publish data to the DAS.

DPP implementation use MongoDB as NoSQL database. DPP REST services communicate with MongoDB using Mongoose. Mongoose is MongoDB Object Data modeling (ODM) for Node.js.

HTTPS is used for communication between DPP REST services and OSRM. While OSRM provide six types of services, our REST services uses only of those services. These are trip service and route service. Using this services of OSRM DPP REST services get information as explained in Section 3.2 .

4.3.1. Authentication

The REST API implemented authentication mechanism is shared key authentication. This authentication mechanism implemented using JSON Web Token (JWT). The JSON web token generate JSON based token using payload and secret key. In DPP, JWT payload includes user username and password. Using JWT algorithm is HMAC SHA256 to encrypt or generate JSON

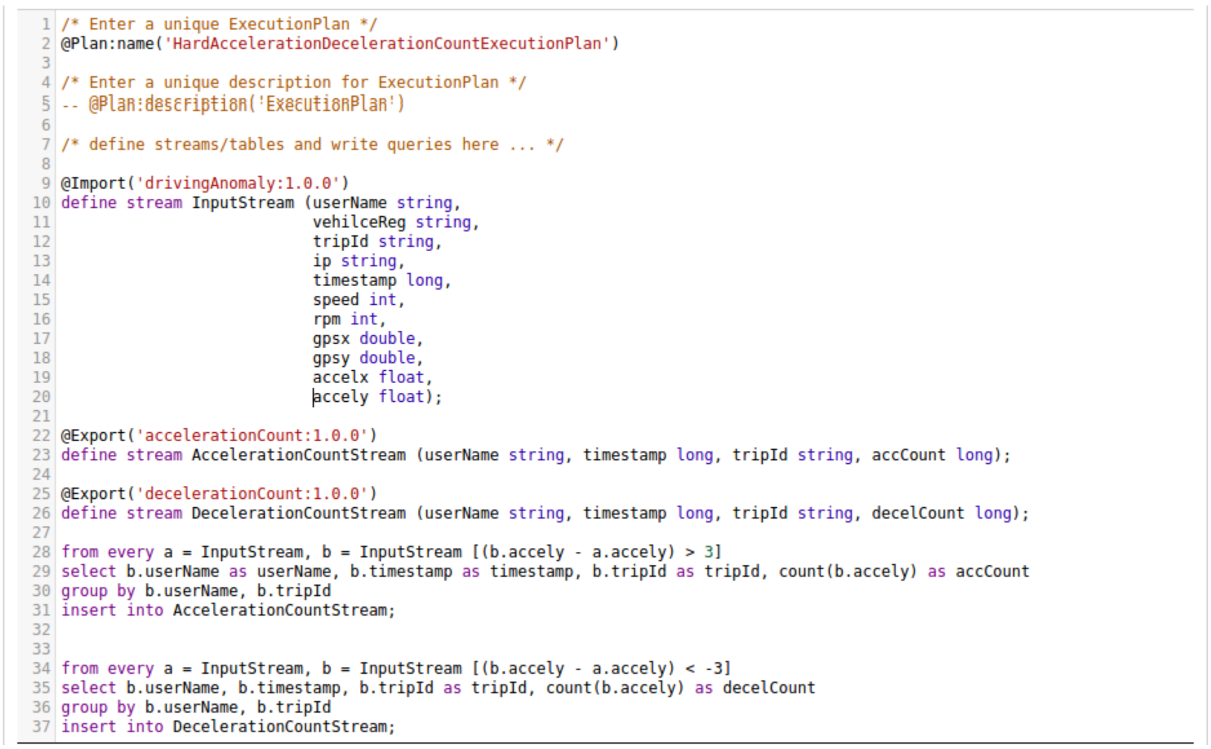
Web Token. The JWT used as a shared key.

Login request of the REST API generate the JWT and this token is send to the client for future API call validation. After the login request, client is expected to attach this token in all future request headers' user authorization tag. Then the REST API verify this JWT before it passes to route (controller).

4.4. Driver Profiling Platform

4.4.1. Real-Time Analysis

As described in Section 3.3, real-time analysis has been implemented on WSO2 DAS. WSO2 DAS has its own real-time event processing engine called Siddhi. All the rules have been implemented using Siddhi queries. Figure 4.2 shows an example rule that is specified as a siddhi query to detect hard acceleration and hard deceleration.



```
/* Enter a unique ExecutionPlan */
@Plan:name('HardAccelerationDecelerationCountExecutionPlan')

/* Enter a unique description for ExecutionPlan */
-- @Plan:description('ExecutionPlan')

/* define streams/tables and write queries here ... */

@Import('drivingAnomaly:1.0.0')
define stream InputStream (userName string,
                           vehilceReg string,
                           tripId string,
                           ip string,
                           timestamp long,
                           speed int,
                           rpm int,
                           gpsx double,
                           gpsy double,
                           accelx float,
                           accely float);

@Export('accelerationCount:1.0.0')
define stream AccelerationCountStream (userName string, timestamp long, tripId string, accCount long);

@Export('decelerationCount:1.0.0')
define stream DecelerationCountStream (userName string, timestamp long, tripId string, decelCount long);

from every a = InputStream, b = InputStream [(b.accely - a.accely) > 3]
select b.userName as userName, b.timestamp as timestamp, b.tripId as tripId, count(b.accely) as accCount
group by b.userName, b.tripId
insert into AccelerationCountStream;


from every a = InputStream, b = InputStream [(b.accely - a.accely) < -3]
select b.userName, b.timestamp, b.tripId as tripId, count(b.accely) as decelCount
group by b.userName, b.tripId
insert into DecelerationCountStream;
```

Figure 4.2: Execution plan of detecting hard acceleration and hard deceleration.

These rules can detect five types of abnormal driving behaviors and when it detects an abnormal driving pattern, it publishes it to dashboard through REST API. Dashboard displays those abnormal driving data as a count, i.e., number of times that each of abnormal driving pattern is detected. Figure 4.3 shows the relevant screenshot. In addition, Siddhi event processor published average speed, acceleration, as well as hard acceleration count and deceleration count to the dashboard. Moreover, these data are persisted in the DAS to display total count of each driving pattern occurred as a summary. Figure 4.3, 4.4 and 4.5 shows a set of screenshots of the dashboard.

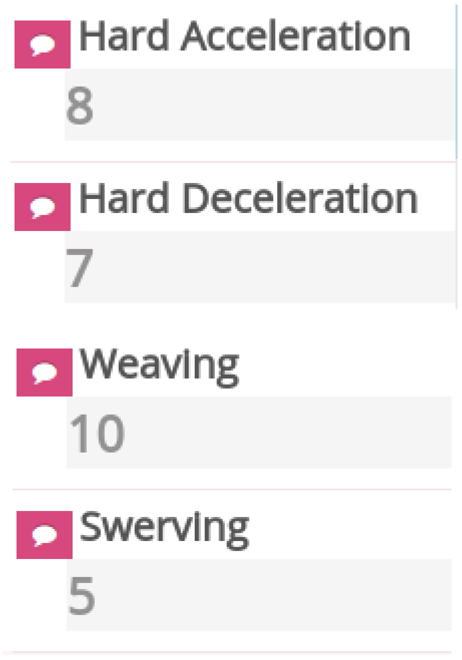

Hard Acceleration
8
Hard Deceleration
7
Weaving
10
Swerving
5

Figure 4.3: Abnormal driving behaviors detection data.

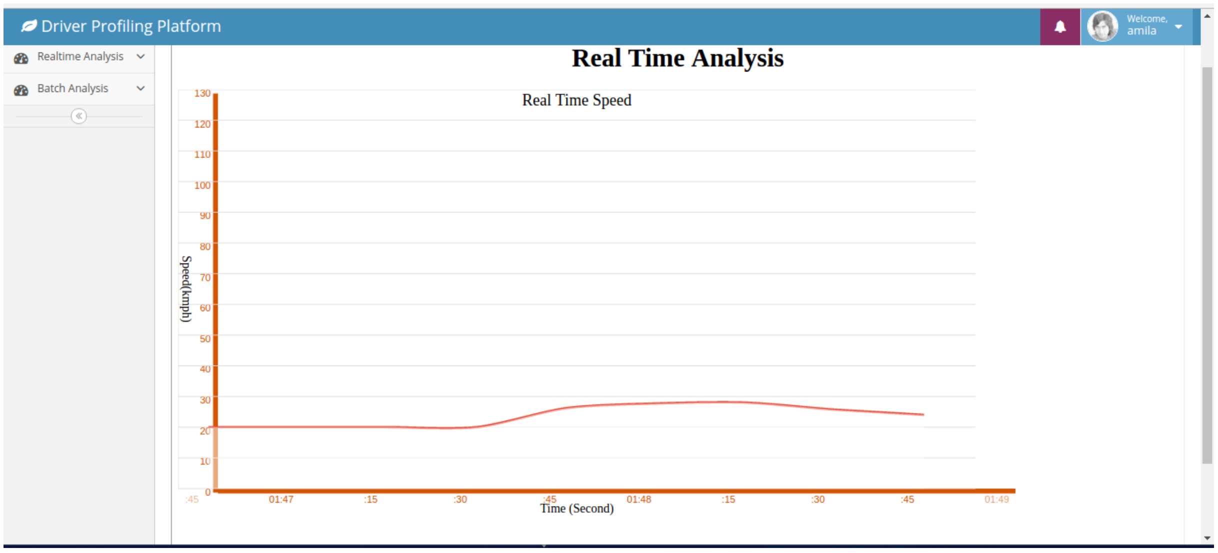


Figure 4.4: Speed variation graph.

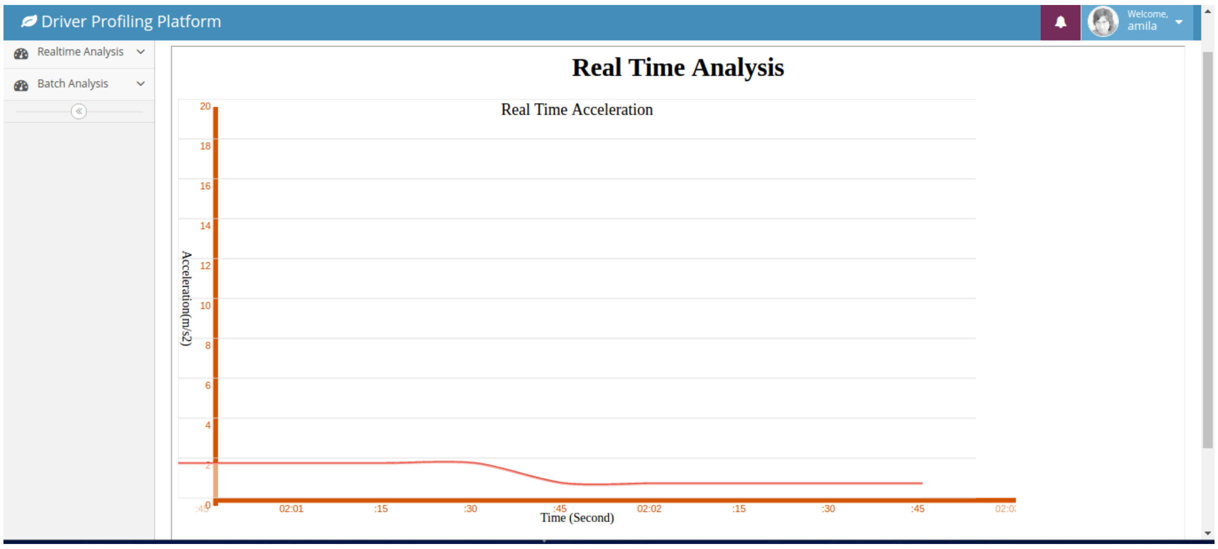


Figure 4.5: Acceleration variation graph.

4.4.2. Historical Analysis

Under historical analysis, we are categorizing drivers according to their long-term driving behaviors using data which were persisted through the real-time analysis phase. As discussed in Sections 3.4.1 and 3.4.2 we provide two solutions under historical analysis. During the implementation of fuzzy logic and skill aggression score methods, we used two separated Spark SQL [18] script which is provided inside WSO2 DAS.

In real-time analysis phase, we persist average speed, x-axis acceleration, y-axis acceleration, and engine RPM. We request those data from the database when the fuzzy logic [11] based solution is performed. Then we calculate the norm of the acceleration according to the way of equation 3.4. Then we calculate the average speed according to the equation 3.5 of the considered time period and send these calculated norm value and average speed to the User Defined Function which is a plugin to the DAS using Java. Based on the given threshold values according to [1], UDF return the category number. Based on the number we classified the given drivers' driving behavior according to the following categories. Such as Below Normal, Normal, Abnormal and Risky.

In the second method, we used MyDrive method [9] to calculate some score values with respect to the driving behavior of particular drivers. We used longitudinal and lateral accelerations, trip ID and speed. Using those details calculate Relative Aggression Score and Relative Skill Score with respect to the Equation 3.2 and 3.3.

We used Spark SQL to perform these calculation parts. Since we want to perform these analysis parts in periodic time, we used cron expressions. Using those cron expression, each script is run once a month and update the above mentioned category details and score values.

4.5. Implementation of Dashboard

Dashboard presents results from both real time and historical analysis via a web application. Main three parts of the dashboard are registering, profiling, and data presenting.

When user request to login, user credentials are sent to the backend through the REST API, then validates the credentials and sends a token. Similar to mobile app, Every request from dashboard to the REST API should provide a valid token. We use such security features to enhance the privacy of the users. To accomplish this, we use browser cookies to store the token details. , For the initial registering phase, user has to send his login authentication details and user type. According to the selected user type, page accessing privileges are added inside of the dashboard. In the first step of the user, after login, he has to complete his profile details and vehicle profile details according to the Figure 4.6 and 4.7.

Angularjs is used to implement the front end functionalities. For the convenience, jquery library also used to enhance the user interactions. Front end User Interfaces are implemented using HTML5. To implement such graph visualizations, we have used D3 which is a powerful javascript library specialized for graph visualization.

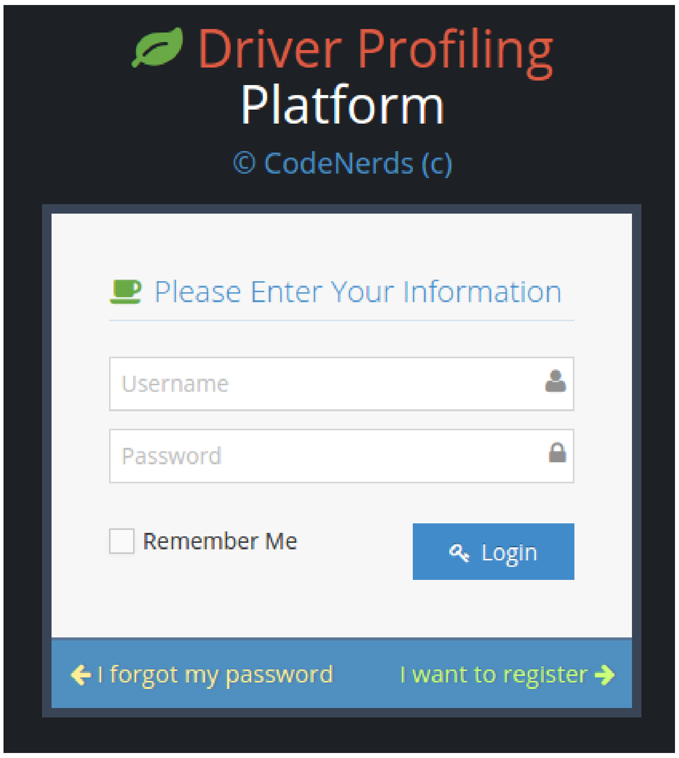
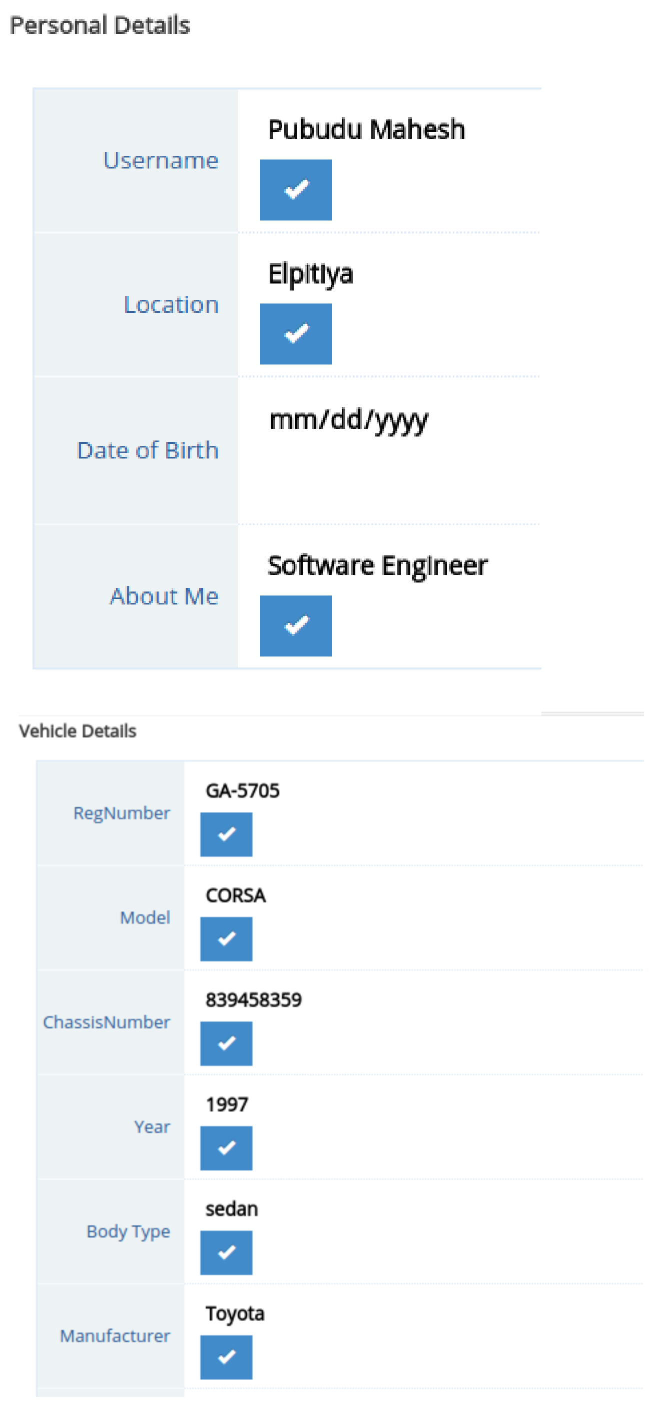


Figure 4.6: User login page.


Personal Details

Username	Pubudu Mahesh ✓
Location	Elpitiya ✓
Date of Birth	mm/dd/yyyy
About Me	Software Engineer ✓

Vehicle Details

RegNumber	GA-5705 ✓
Model	CORSA ✓
ChassisNumber	839458359 ✓
Year	1997 ✓
Body Type	sedan ✓
Manufacturer	Toyota ✓

Figure 4.7: Edit profile details.

User interfaces that the users have access to is determined based on their privileges. For example, if user is logged in to the dashboard, he should not be able to see other members' details for preventing privacy issues of other members. Currently the system supports following user roles:

- Insurer - insurance company, he interact with the system via given API
- Admin - he is like an owner of the vehicle company, can see only the batch analysis data of underneath drivers in the company.
- User - single vehicle owner.

According to the above mentioned privileges, we provided real-time vehicle details only for the *Users* as well as *Admin* can check the historical analytical data of all drivers who have registered in the system. For example, Admin can check current category of all drivers, RSS-RAS scores based classifications of all users.

4.6 Database

For the purpose of analyzing historical data, we need to persist real-time analyzed data and other related data. As we are received data stream every second, we have to persist lot of data instant time and database size growing speed is really high. Therefore, we were not suitable to use a relational database like MySQL. As the solution, we figure out most appropriate solution for the problem is MongoDB engine. In our database it is not required to handle inter dependencies among the database tables. Moreover, latency is really a considerable factor for live data analyzing and visualization part. As the comparison between MongoDB and MySQL, necessity of such MongoDB database engine is really high. MongoDB is an Object Oriented based database engine. Because of these reasons, implementation and handling is very easy with respect to other relational database engines.

5 Results

5.1 Historical Analysis

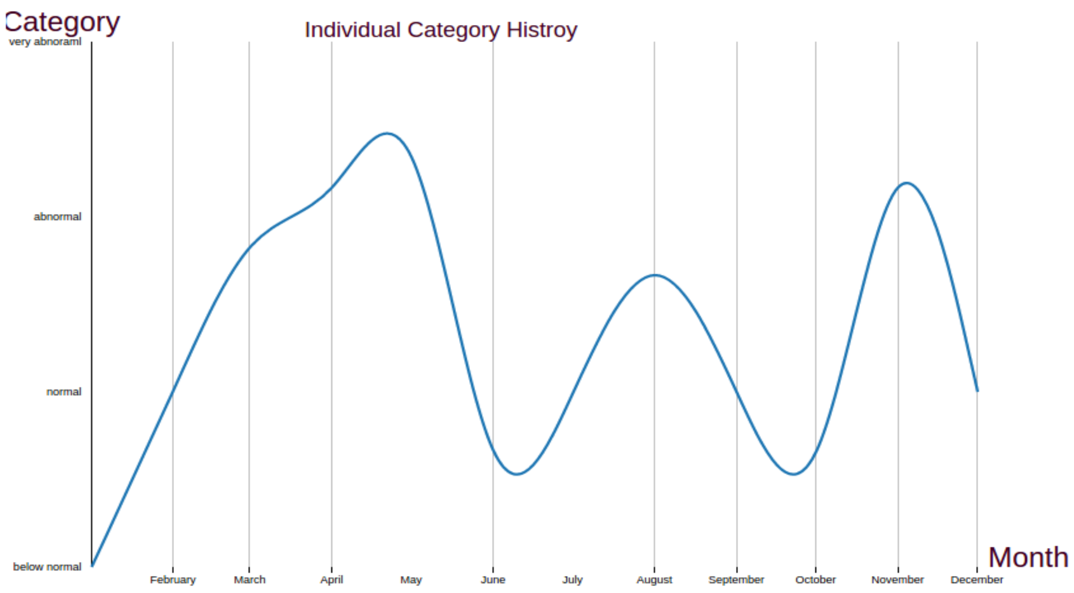
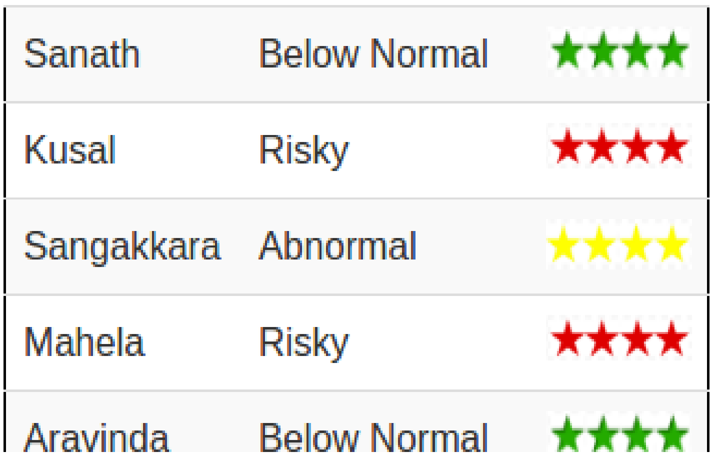


Figure 5.1 : Individual category history.

Figure 5.1 illustrates how the category of a driver changed with time based on his/her driving behavior. This enables driver can check his behavior within last 12 months. Specially, such visualization would be help to the UBI third party users, who are willing to offer insurance premium for the drivers.

As we mentioned the privileges for the admin and users of the system in previous chapter, only administrators are given the checking all details of registered all drivers in the system. Figure 5.2 illustrates the current driving details of all registered drivers in the system.



Sanath	Below Normal	★★★★
Kusal	Risky	★★★★
Sangakkara	Abnormal	★★★★
Mahela	Risky	★★★★
Aravinda	Below Normal	★★★★

Figure 5.2: Current category of all users.

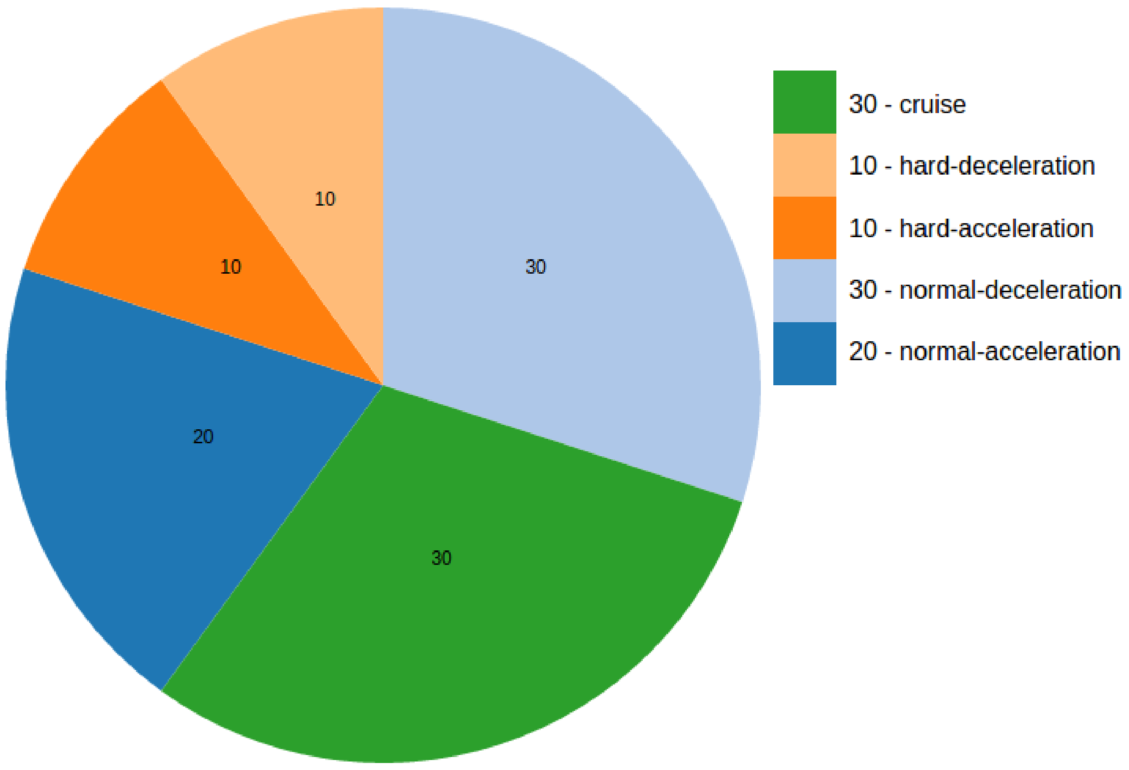


Figure 5.3: Driving cycle.

Driving cycle is indicating the count details of acceleration types which are persisted throughout the real-time analysis. These types of graph are visualized for the purpose of obtaining summary for the latest last trip. So that, such persisted data, would be overwritten once finish the trip. By looking at the pie chart similar to Figure 5.3 even a driver can get an idea about his driving patterns.

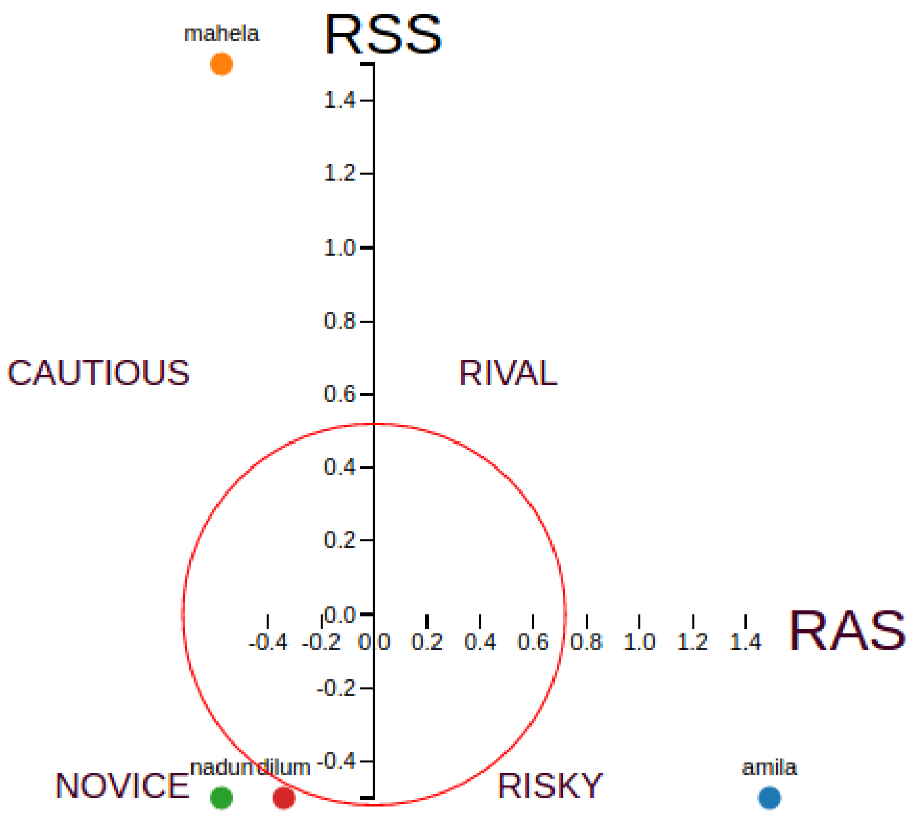


Figure 5.4: RAS vs RSS.

RSS and RAS value are calculated and visualized as in Figure 5.4. With this we were able to identified four categories which are used to classify users which are Risky, Novice, Cautious, and Rival.

5.2 Performance and Accuracy

5.2.1 Real-time Analysis

To evaluate the accuracy of five rules that are used to detect real-time driving anomaly behaviors, we collected real data from a vehicle and obtained the data through the OBDII dongle and persisted all records in the mobile phone as CSV files. While we were collecting data, we also used dashboard camera to get synchronous video streams with respect to the collecting data. Based on both OBDII and video data we calculated the accuracy of detection. For this we labeled the video through visual inspection for anomalous driving. In evaluation stage, when we run the result set, system was able to identify the anomaly driving behaviors.

Since there are no existing labeled data, we had to drive a vehicle and obtained the data through the OBDII dongle and persisted all records in the mobile phone as CSV files. While we were collecting data, we also used dashboard camera to get synchronous video streams with respect to the collecting data. Based on both OBDII and video data we calculate the accuracy of detection. In our driving session, it was not practicable to intentionally act abnormal behaviors other than sudden acceleration and sudden deceleration. Therefore the amount of other abnormal behaviors was low compared to them.

Table 5.1: Performance tables

Driver: Amila

CSV		Sudden Accelerations	Sudden deceleration	Weaving	Swearing	Slide Slipping	Wide Turns
0	Actual	4	2	-	-	-	-
	Detected	1	2	-	-	-	-
1	Actual	2	2	-	-	-	-
	Detected	3	5	-	-	-	-
2	Actual	5	3	1	-	-	-
	Detected	4	3	-	-	-	-
3	Actual	4	6	-	-	-	-
	Detected	7	3	-	-	-	-
4	Actual	3	6	-	-	-	-
	Detected	4	5	-	-	-	-
5	Actual	4	9	-	-	-	-
	Detected	4	5	-	-	-	-
6	Actual	5	7	-	-	-	-
	Detected	3	4	-	-	-	-
7	Actual	3	5	-	-	-	-
	Detected	2	4	-	-	-	-
8	Actual	3	2	-	-	-	-

	Detected	5	7	-	-	-	-
9	Actual	6	4	-	-	-	-
	Detected	7	9	-	-	-	-
Sum	Actual	39	46	1	-	-	-
	Detected	61	59	-	-	-	-

Driver: Dr. Dilum

CSV		Sudden Accelerations	Sudden deceleration	Weaving	Swearing	Slide Slipping	Wide Turns
0	Actual	6	5	-	-	-	-
	Detected	5	4	-	-	-	-
1	Actual	8	3	-	-	-	-
	Detected	7	6	-	-	-	-
Sum	Actual	13	8	-	-	-	-
	Detected	7	9	-	-	-	-

Driver: Nadun

CSV		Sudden Accelerations	Sudden deceleration	Weaving	Swearing	Slide Slipping	Wide Turns
0	Actual	9	7	-	-	-	-
	Detected	3	3	-	-	-	-
1	Actual	3	7	-	-	-	-
	Detected	5	4	-	-	-	-
2	Actual	8	5	-	-	-	-
	Detected	3	2	-	-	-	-

Sum	Actual	20	19	-	-	-	-
	Detected	16	8	-	-	-	-

Driver: Pubudu

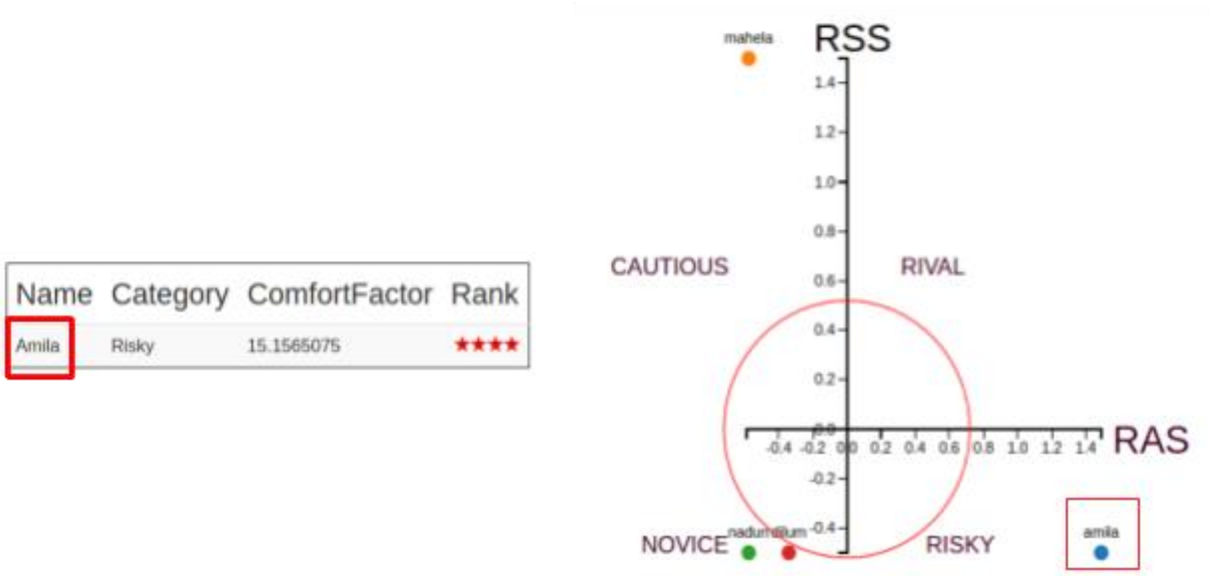
CSV		Sudden Accelerations	Sudden deceleration	Weaving	Swearing	Slide Slipping	Wide Turns
0	Actual	8	5	-	-	-	-
	Detected	9	7	-	-	-	-
1	Actual	4	3	-	-	-	-
	Detected	3	9	-	-	-	-
Sum	Actual	12	8	-	-	-	-
	Detected	16	16	-	-	-	-

According to the video streams, that we have used to detect driving behaviors, we encountered some abnormal driving behaviors. Most of cases, we were able to guessed sudden acceleration and sudden decelerations as the abnormal driving behaviors. But, in some cases, we guessed, weaving as the abnormal driving behavior according to the prior knowledge of driving anomaly behavior.

But in most of cases, the implemented system was unable to detect such weaving and other related anomaly behaviors, other than, hard accelerations and hard deceleration

Overall: Acceleration (A/D): 84 / 100 = 84%
Deceleration (A/D): 81 / 92 = 88.04

5.2.2 Historical Analysis



Name	Category	ComfortFactor	Rank
Amila	Risky	15.1565075	★★★★

Figure 5.5: Result comparison between MyDrive vs. Fuzzy logic.

We are performing historical analysis of drivers using two techniques. As can be seen in Figure 5.5 both techniques produced consistent results. For example, after performing the fuzzy logic implementation, category of user “amila’ is “risky” and MyDrive method also categorizes “amila” as a Risky driver.

6. Summary

6.1 Conclusions

With the emergence of IoT, developing a system to retrieve vehicular data and provide analysis on drivers based on them could effectively address the current issues in Usage Based Insurance (UBI) field and in return it could lead to increase the number of disciplined drivers. As the outcome features of the project, we are providing live and historical data analysis part for each registered drivers and historical data analysis results of all drivers are given to the administrative users. In addition to that we are sending alert notification to the driver when he is categorized as risky driver.

Because of the proposed solution, effective social outcome can be achieved by identifying risky behaviors of drivers promptly notifying the drivers. As further, thinking about the financial return, effective driving behavior directly lead to lower premium for effective drivers. So both social outcome and financial return exists with regarding such systems can be called social investment.

6.2 Challenges

We used DAS Spark terminal to implement the historical data analysis. However, we faced limitations with DAS Spark terminal. For example, we were not able to handle variables inside the terminal. As a solution, we have implemented a plugin for the DAS. It was a Java-based User Defined Function (UDF). Even in this case we were unable to handle double values between UDF and the Spark. We have to convert all double values to float inside the SPARK manually and need to convert again those things again inside the UDF.

When we were in the implementing the dashboard, we have to communicate with REST API. However, we experienced ‘cross domain issue’, where dashboard and REST are published on separated domain. Because of that, we were not able to use HTTP request between these domains.

6.3 Future work

Currently the mobile application supports only the Android platform. In future, it can be upgraded to support other operating systems such as iOS and Windows or perhaps go with a cross-platform version. The alerts given to the driver can be converted to audible alerts. Generating alerts as Android notifications in the mobile screen could be changed as to be speaking alerts where driver will not have to look into the mobile screen. When the driver enters to a dead-zone where there is no network coverage, currently the application stops sending payloads as it receives no response from the central server. After the dead-zone, the driver has to manually switch-ON server connectivity. This can be developed further such that when a dead-zone is reached, the application buffers the payloads till the dead-zone ends and then sends them notifying that payloads were delayed due to the dead-zone.

Running the mobile app and having both bluetooth and mobile network connections may significantly affect power consumption. The alternative for this is that the application can be modified to be added for the vehicles which have Android-based car multimedia players and digital rearview mirrors. Although the number of vehicles with Android multimedia players are low at the moment, with the introduction of Android Auto [17], most of the vehicle manufacturers are likely to be adding Android-enabled multimedia players. Therefore, researching on how to integrate the mobile application with it will be a good investment as well.

The current system can detect only five types of abnormal driving behaviors. It can be extended by adding more abnormal driving behavior detection rules. One of such abnormal driving behavior is taking fast u-turn. Currently, driving time, driving areas, traffic condition, and weather conditions are not considered when analyzing the driving data. These things can be considered when doing real-time analyzation to get high accuracy results because these thing also affect for the driving behaviors. In addition, only time and acceleration data have been used for real-time analyzation. We can use more vehicular data such as engine RPM, GPS data, steering wheel movements, etc., to monitor abnormal driving behaviors.

The implemented system of batch analysis part, we are using few models. At the moment, models are not updating with respect to the user. Which means, each and every users are categorized under one model. As further improvement of the historical analysis, we can implement the model to update dynamically with respect to the drivers.

In MyDrive method, we have already implemented two ways of generating scores for the driver's driving behaviors. Such as peer group analysis and individual analysis part. As an improvement, we can suggest a method to implement, regarding the driver's trip levels.

When we are categorizing and calculating scores for the drivers, considered only a few inputs. Such as x-axis acceleration, y-axis acceleration, and average speed as further improvement for the analysis models, we can manipulate extra vehicular data. Such as throttle position and engine RPM. In addition to the vehicular data, we are using GPS data to calculate the total distance which particular driver has driven through the considered time period. As further improvement, we can feed some other data such as road conditions, road type details, and whether condition of the vehicle driven area to the model to categorizing and calculating scores for the driver, as those details also would be critical for his driving pattern. Because the driving behaviors of other closed vehicle when we are in the road, are affect to our driving patterns, it would be more optimizing solution, if we are able to use their driving patterns through sensors like ultrasonic sensors and dashboard cam video.

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