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Road Rage and Aggressive Driving Behaviour Detection in Usage-Based Insurance Using Machine Learning

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ABSTRACT

Driving behaviour is a critical issue in modern transportation systems due to the increasing concerns about the safety of drivers, passengers, and road users. Machine learning models are capable of learning driving patterns from sensor data and recognizing individuals by their driving behaviours. This paper presents a novel framework for aggressive driving detection and driver classification based on driving events identified from GPS data collected with smartphones and heart rate of the driver captured with a wearable device. The proposed system for road rage and aggressive driving detection (RAD) is realized with an integral framework with components for data acquisition, event detection, driver classification, and model interpretability. The system is implemented by generating a prediction model by training machine learning classifiers with a dataset collected in a cohort to classify drivers into good, unhealthy, road rage, and always bad. The proposed system is to improve road safety and to customize insurance premiums in the best interest of policy holders and insurance companies.

KEYWORDS

Big Data, Driver Behaviour, Driver Monitoring, Interpretable Machine Learning, Manage-How-You-Drive, Usage-Based Insurance

INTRODUCTION

Driving behaviours are the main cause of road accidents and one of the main sources of insurance claims. To improve road safety and reduce the number of insurance claims, it is important to identify driving behaviours in order to adapt the insurance contract accordingly. Identifying abnormal driving behaviour is an important task for Usage-Based Insurance (UBI) companies as it can help them to assess a customer's risk and price their policies accordingly. Driving behaviours such as speeding and aggressive and careless driving are of particular interest to UBI companies as they are directly related to an individual's risk of an accident. Car driving behaviours can be measured by data such as speed, acceleration/deceleration, lane position and headway. Accident proneness refers to a

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general disposition or personality trait that increases the likelihood of an individual being involved in an accident (Shinar, 2017). Differences in accident proneness are generally caused by a number of factors, such as gender, age, personality traits, driving experience, attitude towards driving, road conditions and environmental stimuli. Figure 1 illustrates the factors influencing driver behaviour.

Driving style is defined as a habitual driving behaviour, characterizing a driver's tendencies to behave in specific ways on a regular basis (Sagberg et al., 2015). It also describes how a driver's driving style affects the safety of the individual and others on the road. The identification of such habits has become increasingly important for the development of insurance companies as it can help them to identify high-risk drivers, estimate risk and set an insurance premium accordingly.

Abnormal driving is generally characterized by atypical or risky behaviour that is not in line with the norms for a particular group of drivers (Hu et al., 2017). There are a number of different types of abnormal driving, but the most relevant for UBI are those that are associated with an increased risk of an accident, such as speeding, aggressive driving and careless driving. Road rage is a brief, intense reaction to perceived provocation in a situation of conflict between two or more persons on the road, characterized by verbal abuse, shoving, hitting, threatening and possibly minor or major physical aggression (Shinar, 1998). Aggressive driving is characterized by hostile, impatient and risky behaviour such as speeding, tailgating, weaving in and out of traffic and running red lights.

The World Health Organization (WHO) report on road traffic injuries reveals that around 1.3 million people die in road crashes every year (WHO, 2022). These crashes are identified as causing around 3% loss of Gross Domestic Product (GDP) in most countries. Further, 20 to 50 million people are susceptible to injuries, resulting in disabilities and long-term health conditions. Figure 2 depicts the fatalities in road accidents over the past few years, which are increasing every year. Along with the Bloomberg Initiative for Global Road Safety (BIGRS), the WHO strives to reduce fatalities and help governments develop a long-term sustainable plan for safety and road traffic injury prevention, and define guidelines and principles of a comprehensive road safety approach. Technological interventions in road rage and aggressive driving behaviour are crucial for this objective.

Recent developments such as Drivesafe (Bergasa et al., 2014), a mobile application for alerting and ranking drivers, and Advanced Vehicle Technology (AVT) have led to the development of assistive mechanisms in the detection and reduction of aggressive driving (Furlan et al., 2020; Benson et al,, 2021). AVTs include a wide range of technologies such as anti-collision systems, automatic

Figure 1.
Factors Influencing Driving Behaviour

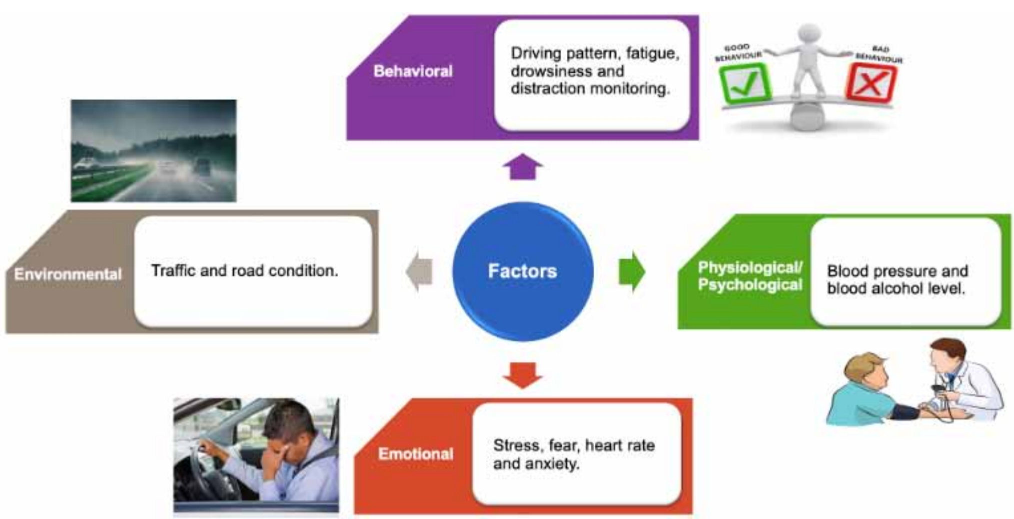
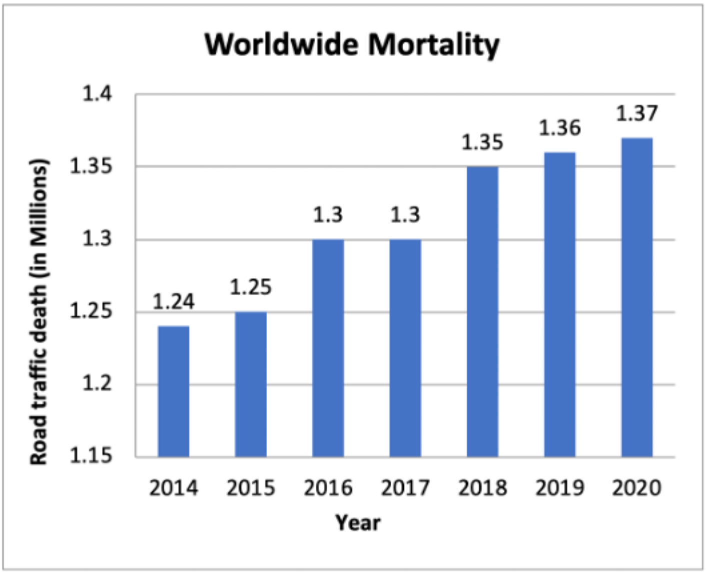


Figure 2.
Yearly Fatalities in Road Accidents



emergency braking, blind spot monitoring, lane departure warning, forward collision warning, lane change assistance, and adaptive cruise control systems. However, the effectiveness of AVTs in reducing aggressive driving behaviour is still unknown and there exists a possibility of it becoming a distractive technology, frustrating untrained drivers.

Traditionally, motor insurance pricing (Kafková & Křivánková, 2014) is performed with Generalized Linear Models (GLM) (Nelder & Wedderburn, 1972) such as logistic regression (LR), Poisson regression, Cox proportional hazards model, etc. These models use demographic information (e.g., age, gender, marital status, etc.), driving record (e.g., number of accidents, tickets, etc.) and vehicle type as predictors of risk, called the 'priori information'. Later, posterior information about the policyholder is obtained from historical claims data (e.g., total claims costs, number of accidents) or population data (e.g., market share, insurance penetration rate, etc.). This information is used to determine the expected cost, total loss, etc. for a given policyholder as described in the works of Gao et al. (2021) and Corradin et al. (2022).

However, GLMs do not possess the flexibility to learn complex effects from multiple causes as they model only interaction between two factors. In a recent investigation, Blier-Wong et al. (2020) have projected the limitations of the usage of GLM in evaluating the risks in property and casualty insurance (P&C) covers that involve multiple behaviour causes. The authors advocate the usage of machine-learning approaches to overcome the drawbacks of GLM models.

Machine-learning models are capable of learning non-linear functions and have shown greater success in modelling complex relationships between inputs and the targeted output. Further, they can handle unstructured data, characteristic of insurance portfolios. Therefore, algorithms that work with training reactive features using data from past claims that have been laid for other policy holders, can help to build a robust risk model. Grize et al. (2020) emphasize the significance of the usage of machine-learning approaches in the insurance vertical when modelling the analytical applications such as risk estimation, premium calculation, profitability monitoring and risk modelling.

Inspired by the pioneering and recent works advocating the usage of machine-learning approaches in the insurance business (Dietterich, 1997; Bian et al., 2018), this research explores the possible uses of machine-learning models in RAD, based on multiple behavioural causes for UBI-related claims. The contributions of this research are as below:

1. This research proposes a novel framework for RAD based on the behavioural, environmental, emotional and physiological/psychological factors of an individual for UBI policy planning.
2. Conventional machine-learning models such as DT (Quinlan, 1996), RF (Breiman, 2001) and SVM (Cortes & Vapnik, 1995) are modelled as multiclass classifiers to categorize drivers into four types such as *good, unhealthy, road rage* and *always bad.*

The proposed framework and the models evaluated with real-time data generalize well with arbitrary data captured in a cohort in India, suggesting the feasibility of deploying such models for RAD in other geographies.

This paper is organized as follows. Section 2 presents a comprehensive review of driver behaviour modelling and applications of machine-learning approaches in the insurance industry. Section 3 presents the mathematical representations of the machine-learning models employed in this research. The proposed framework is described in section 4, and experimental results with illustrations, interpretations and comparative analysis are presented in section 5. The paper is concluded with directions for further research in section 6.

RELATED WORK

This section presents an inclusive analysis of literature spanning the earliest to the most recent representative works in the context of this research. Over the past two decades, several approaches for automated driving behaviour monitoring have been proposed (Ji et al., 2004; Al-Sultan et al., 2013). With the evolution of telematics insurance models in which premiums are calculated based on the data collected from vehicle-mounted devices and risk profiles of drivers, Manage-How-You-Drive (MHYD) insurance schemes have become popular (Cieślik, 2017).

Generally, driver patterns are monitored with GPS devices, On-Board Diagnosis (OBD) sensors and smartphone sensors. However, GPS is a passive device and thus is vulnerable to various sources of noise and interference, and GPS-based driver pattern monitoring has been limited to only specific purposes, e.g., driving route tracking and vehicle detection (Chowdhury et al., 2018). OBD sensors such as throttle, brake and steering wheel angle sensors are widely used to collect data from the vehicle (Amarasinghe et al., 2015). Compared with OBD sensors, smartphone sensors have much better data quality due to their higher signal-to-noise ratio and immunity to the power fluctuations of the vehicle (Samuel et al., 2021). As a result, a lot of research has been carried out to monitor driving patterns using smartphone sensors. Driver behaviour modelling (AbuAli & Abou-zeid, 2016; Chen et al., 2019) has been a long-standing area of research with many studies proposed in the past decade towards understanding and detecting driver behaviour anomalies to improve road safety. Several studies have been carried out to identify the features of aggressive driving and road rage incidents and evaluate their effects on insurance pricing (Peng et al., 2015; Gvozdenović and Uzelac 2018; Arumugam and Bhargavi 2019; Naik and Sikka 2021). Further, the outbreak of COVID-19 has considerably affected the road traffic statistics. Insurance companies are facing challenges in risk assessment, policy pricing, personalized claims, etc. due to the fluctuation in accident statistics during COVID-19. A few studies on the impact of COVID-19 on the insurance industry call for adaptation of digital technologies, new data-driven models, telematics and other technologies to achieve a balance between customer experience and business continuity (Katrakazas et al., 2020; Babuna et al., 2020; Volosovych et al., 2021).

The Driving Behaviour Detection and iDentification system (D^3) (Yu et al., 2016) identifies six kinds of abnormal driving behaviours such as fast U-turn, sideslipping, sudden braking, weaving, swerving and turning with a wide radius. SafeDrive (Zhang et al., 2017) is a cloud-based driver anomaly detection system based on unsupervised learning, implemented in the Internet-of-Vehicle (IoV) platform. A driving model for quantification of driving style proposed by Shi et al. (2015) is personalized to a driver based on the vehicle and the road conditions.

A model for driving behaviour visualization proposed by Liu et al. (2017) is based on the hypothesis that a few essential features generate multivariate data to model driving behaviours. An approach for driving event detection and driver profiling detects lateral and longitudinal driving manoeuvres with Hidden Markov Models (HMM) and jerk energy technique respectively (Daptardar et al., 2015). A multi-type data-based framework to access the driving risk level for UBI proposed by Yin and Chen (2018) employs a set of kernels to capture attributes. A predictive (Arun Kumar & Yellampalli, 2018) model for auto insurance based on binary LR, called black box, uses GPS data.

Six classification models are proposed by Brahim et al. (2022) for driver behaviour classification into four categories: intermediate, aggressive, dangerous and normal. A framework for driver behaviour and driving pattern modelling based on driver, vehicle and environmental parameters also advocates the application of various ML approaches (Malik & Nandal, 2021). Two most recent works on the application of predictive analytics in the insurance sector show that customer satisfaction, reduction of operation costs and detection of fraudulent claims can be considerably improved with ML models (Sharma et al., 2022; Prajapati, 2022).

A detailed review of the above shows that UBI is the emerging model of personal insurance and will replace the traditional pooling-based models in the near future. It is understood that complexity in risk-based premium computation can be reduced with usage information. Risk assessment with ML approaches for modelling driver behaviours, learning driving patterns and predicting risk classification is key to developing UBI models. Few works have shown that models based on multiple attributes outperform models trained with a single attribute. This review identifies the need for robust models for risk assessment and risk classification based on multiple attributes, and this research is aligned with this requirement.

METHODS

The hypothesis of this research is that road rage and aggressive driving detection behaviour can be predicted by training the machine-learning models with multiple attributes characteristic of the driving behaviour and health of a driver.

LR is a statistical technique for developing a predictive model to determine the probability of an outcome in relation to one or more independent variables. LR is a commonly used tool in many disciplines such as economics, biology, epidemiology and medical research. However, the linearity assumption of LR between independent and dependent variables is often not met in many real-world applications, which can lead to inaccurate results. Particularly, in modelling driving behaviours, it is important to account for the nonlinearity of various factors. Compared to LR, machine-learning models such as Decision Tree (DT), Random Forest (RF) and Support Vector Machine (SVM) can better model nonlinear relationships between independent and dependent variables.

The proposed RAD framework is implemented with a component for driver rage detection using a machine-learning model to classify driving behaviours. Three different baseline models described in the following subsections are trained with driving data to classify driving behaviours.

Decision Tree

A ‘DT’ (Quinlan, 1996) is a statistical classification system that learns from a set of instances to sort new instances into one or more classes. The DT algorithm constructs a tree-like structure that represents a decision problem. At the root of the tree is a set of test instances. The DT algorithm then recursively partitions the test instances into subsets according to a test criterion. Each node in the tree is a partition of the test instances and is associated with a label that is the result of applying the test criterion to the instances in that partition. The leaves of the tree are the labels of the test instances. The DT learns to classify new instances by traversing the tree from the root to the leaves.

Given a set of instances $I = \left\{\left(x_1, y_1\right), \ldots, \left(x_n, y_n\right)\right\}$, the DT T is represented as a binary tree with m nodes and l leaves, where x_i is the feature vector and each y_i is the label of instance i. Each node v in T has l_v leaves, and each of these leaves is associated with a label y_j. The decision tree learning method constructs T for a given training set. In the training process, an instance is presented with the corresponding feature vector x. Then the tree T is traversed from the root node to the leaf nodes. For each node v of the tree, the algorithm decides whether to branch to the left or the right child. For each node v of the tree, the algorithm determines a partition p_v of the training instances and computes a weight w_v associated with the partition. The partition p_v is defined by the values of feature vectors in the partition. The algorithm also determines a label y_v for each partition. The label of the instance is determined by the highest weight of the partition, in equation (1):

$$y_v = \underset{j}{argmax}\left\{w_v \;\; x_j \in p_v\right\} \tag{1}$$

Random Forest

The RF algorithm (Breiman, 2001), is a machine-learning technique used for classification and regression. It computes a series of tree classifiers called DTs, each consisting of a set of rules for classification. The algorithm works by generating a large number of classifiers, each constructed using a different set of features and a different sample of training data. The randomness in the algorithm consists in the fact that each classifier is constructed using a different set of features. The mathematical description of the RF classifier is given as below.

It follows a nonparametric regression framework in which each input vector X is first mapped to a feature space, then to a decision space via a feature mapping function $f : X \to f\left(X\right)$, then to a response space via a response mapping function $g : f\left(X\right) \to g\left(f\left(X\right)\right)$ and finally the response vector Y is obtained by applying a response function $h : g\left(f\left(X\right)\right) \to h\left(g\left(f\left(X\right)\right)\right)$.

For a given training sample $D = \left\{\left(X_1, Y_1\right), \ldots, \left(X_n, Y_n\right)\right\}$, a set of classification trees $T_1, \ldots, T_n$ are constructed as follows. Each tree T_i is a binary tree, where each internal node is labelled by a feature of the input vector X_i and each leaf node is labelled by a class label Y_i. A training sample is first mapped to the input space using f, then to the decision space using g, and finally to the response space using h. Finally, for each tree T_i, the response Y is predicted as a majority vote over all the leaf nodes. For classification problems, the response is set to the class with the largest number of votes, and for regression problems, the predicted response is the average response over all the trees.

Support Vector Machine

A Support Vector Machine (SVM) is a supervised learning algorithm used for classification and regression. It is a type of kernel machine-learning algorithm that uses a kernel function to calculate the distance between two points in a feature space. SVMs are popular for text classification and image recognition tasks. The SVM algorithm works by finding a hyperplane that separates two classes of data as efficiently as possible. The hyperplane is the plane that maximizes the distance between the two classes of data. Points that lie on the hyperplane are classified as belonging to one of the classes, and points that lie outside the hyperplane are classified as belonging to the other class.

The binary SVM classifier constructs a hyperplane to separate two classes labelled $y = \left(-1, +1\right)$ from each other. An SVM has a decision function as in equation (2) where, $K\left(x_i, x\right)$ is a kernel function for $x_i, y_i, i = 1, \ldots, n$ is a class label, $a_i \in \mathbb{R}$ and $b \in \mathbb{R}$ are hyper-parameters, and K is a Gaussian kernel given by equation (3) where σ is a kernel parameter:

$$f\left(x\right) = \sum_{i=1}^{n} a_i y_i K\left(x_i, x\right) + b \tag{2}$$

$$K\left(x_i, x\right) = \exp\left(-\frac{1}{2\sigma^2} \parallel x_i - x \parallel^2\right) \tag{3}$$

A Multiclass SVM (MSVM) (Weston et al., 1998) is a variant of SVM for one-vs.-one or one-vs.-all multiclass classifications. The one-vs.-one MSVM uses a separate binary SVM for each pair of classes and the one-vs.-all MSVM uses a single binary SVM for each class.

The one-vs.-all MSVM used in this research is trained in two phases:

1. Classifying all training points into one of the k classes; and
2. Classifying the remaining points into one of the remaining $k - 1$ classes.

The training data is assumed to be $\mathcal{D} = \{\left(x_i, y_i\right)\}_{i=1}^{m}$, where $x_i \in \mathbb{R}^d$ and $y_i \in \left\{-1, +1\right\}$.

The ℓ_2 regularized linear SVM used in this research solves the optimization problem defined in (4):

$$\begin{aligned} &\min_{\{a_i, b\}} \frac{1}{2} \parallel x - x^* \parallel^2 + C\sum_{i=1}^{m} y_i \parallel a_i \parallel_2 + C\sum_{i=1}^{m} y_i \parallel b \parallel_2, \\ &subject\ \ to\ \ y_i x^T a + b \geq 1 - \gamma \end{aligned} \tag{4}$$

where $C > 0$ is a trade-off parameter, x^* is a separating hyperplane and $y_i x^T a_i \geq 1 - \gamma$ for $i = 1, \ldots, m$.

PROPOSED RAD FRAMEWORK

Problem Definition

Abnormal driving behaviours such as reckless and aggressive driving are usually one of the reasons for accidents, which are considered common offences in several countries. UBI is a risk-based insurance model that monitors driving behaviour of a driver on a particular road in real time, which helps insurers to identify potential risks, predict possible accidents in the near future and compute the premium. Unlike the conventional insurance models that classify the drivers into two or three categories based on historic driving data, static speed limits and fixed premiums, a UBI business model dynamically changes the insurance premiums for each driver, based on real-time driving behaviour.

Recently, the outbreak of COVID-19 has significantly reduced the driving activities of millions of people. Usage-based premium computation, which is the mainstay of the UBI business model, is data-driven. UBI companies are now confronting the challenging problem of detecting abnormal driving behaviour of people from limited on-road data (i.e., the time and date of the on-road events) that are either collected manually or through the network of fixed roadside vehicle detection systems. Risk detection based on behavioural, environmental, physiological and emotional factors can help insurance companies to provide personalized insurance premiums and to support drivers in making better decisions. To this end, a combination of machine learning and data science techniques is required to construct such a model.

Foreseeing the growing trend of UBI business models in the future, this research proposes the RAD system to overcome the drawbacks of the conventional models. The proposed model is realized as a multiclass classifier for driver categorization with the following objectives:

- To collect the driving data from the live driving environment with the GPS and wearable devices using smartphones.
- To classify the drivers into four categories such as *good, unhealthy, road rage* and *always bad*:
    - Good drivers – drivers with an overall driving score above the threshold.
    - Unhealthy drivers – drivers reported as having health problems.
    - Bad drivers – drivers with a poor driving score, who exhibit consistent irregularity in driving and who have received more warnings.
    - Road rage/aggressive drivers – drivers who exhibit road rage and aggression, thus have a higher potential for road accidents.
- To provide alerts, suggestions or warnings to drivers when they are driving abnormally, to prevent road accidents.

A classification diagram in Figure 3 illustrates the role of the proposed RAD system in insurance pricing.

Proposed RAD Architecture

The proposed RAD architecture consists of four components: data collection, rage and aggression detection, interpretability and UBI calculation, as shown in Figure 4. The data collection component collects the driving data from different drivers in real time. The rage and aggression detection component is trained to classify the drivers from the data collected in real-time. The explainable interpretable engine provides explanation on the behaviour of the RAD component in discerning the drivers based on the data. The UBI calculation engine provides insights to the insurance companies, which then calculate the personalized premium for the individuals. The functions of the individual components are illustrated with Figure 5 and described in the following subsections.

Driving Data Collection

Data is collected from the driving environment in real time by using an iOS app, developed with iOS/Swift 3.0 technology and installed on the smartphone of the driver. A cloud instance is created and

**Figure 3.
Classifications of MHYD**

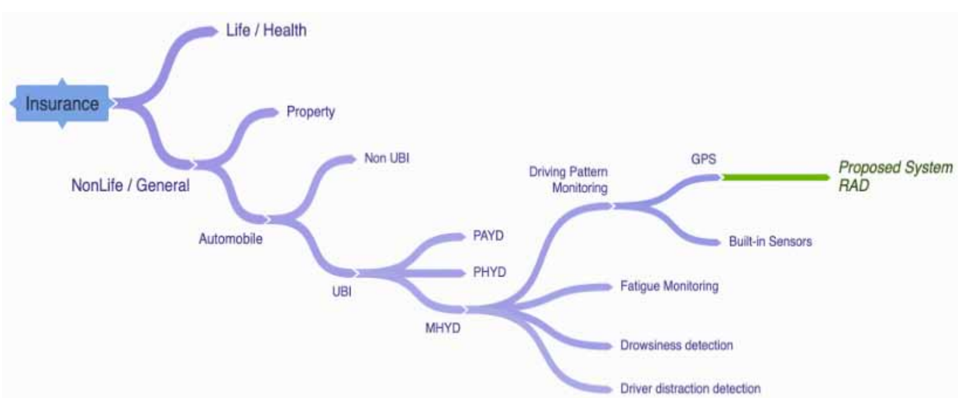


Figure 4.
Proposed RAD Architecture

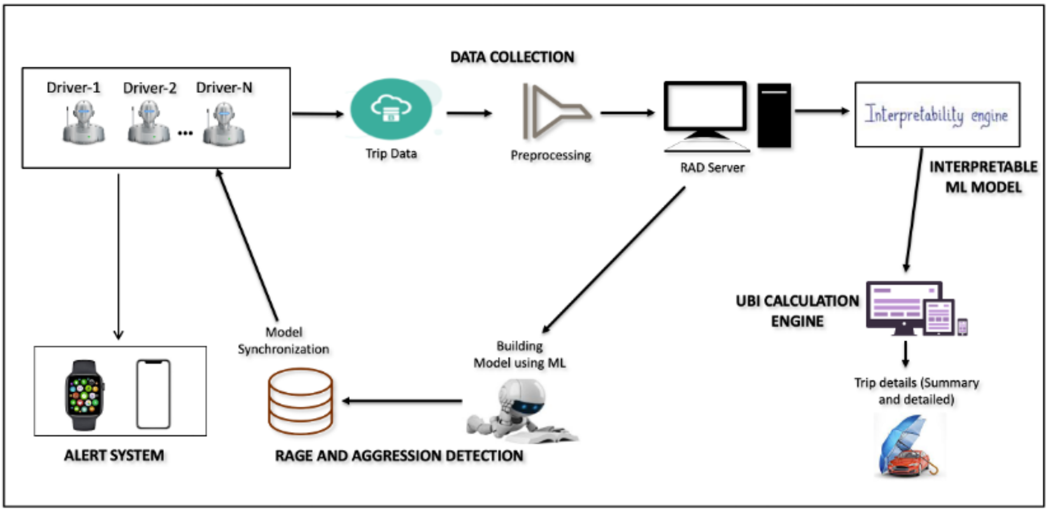
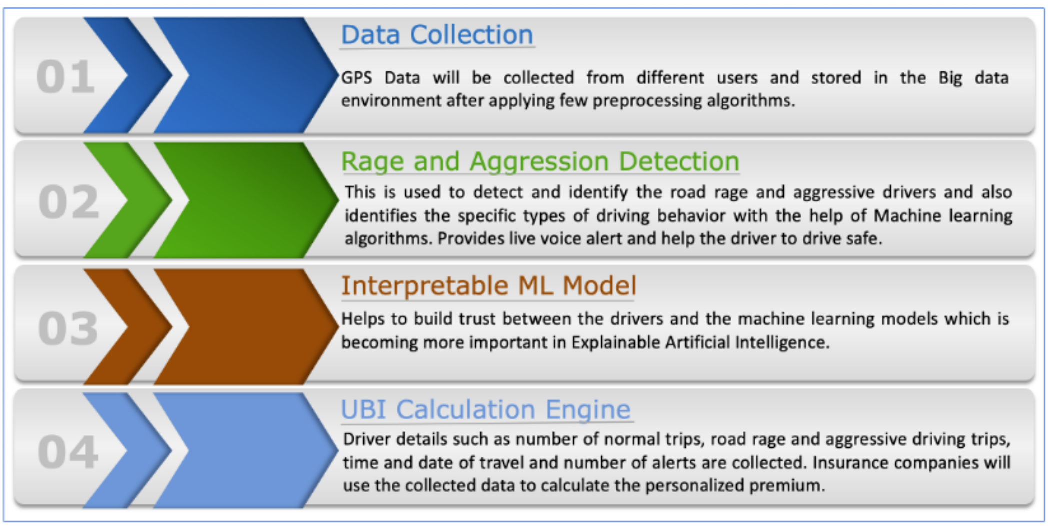


Figure 5.
Functions of RAD Components



big data/machine-learning technologies are installed in the machine. As soon as the driver starts the vehicle, the data collection mechanism collects the data using the iOS app, with the help of GPS signals and a wearable device. This app will start logging the trip details as soon as driver starts the vehicle and continue until the driver stops the vehicle. A trip is characterized as a drive from a source point to a destination, the details of which are sent to the cloud environment for further processing. Swift 3.0 allows users to configure the desired accuracy of location information with a set of predefined constants. In this research, kCLLocationAccuracyBest is used to capture the location at the best accuracy. This content is added to section 4.2.1.

Rage and Aggression Detection

The RAD process is realized in two sub-phases, namely model generation and prediction. Model generation refers to building a classifier model by training a naïve classifier with driver data. In this research, three classifiers are built with three separate machine-learning models, as discussed in section III. Before training, the missing values are filled with valid values and the data samples are normalized. The trained model is run in the driver's device and synchronized every 24 hours. The arbitrary real-time data samples captured are classified into one of the four driver categories assigning the target labels, and personalized voice alerts are provided for the unhealthy and rage/aggressive drivers.

In RAD, the data flow is seen as a series of transformations of the driver data captured by the data acquisition devices as it passes to the other components until the driving behaviour is classified, as shown in Figure 6. The web portal is developed to check the details about a particular driver at any instant in time. A middleware and integration layer uses a few Representational State Transfer (REST) web services to handle the data flow between the data collection and classification layers.

Interpretability

A critical part of artificial intelligence/machine learning is to understand how models arrive at their decisions. This helps to build trust between the humans and the machine-learning models, allowing the user to confide in the system. Interpretability can be achieved using data-centric visualization, providing additional information about the decision, generating example input/output data, etc. In this research, the interpretability engine visualizes the behaviour of the model by analysing the target labels with respect to the input data.

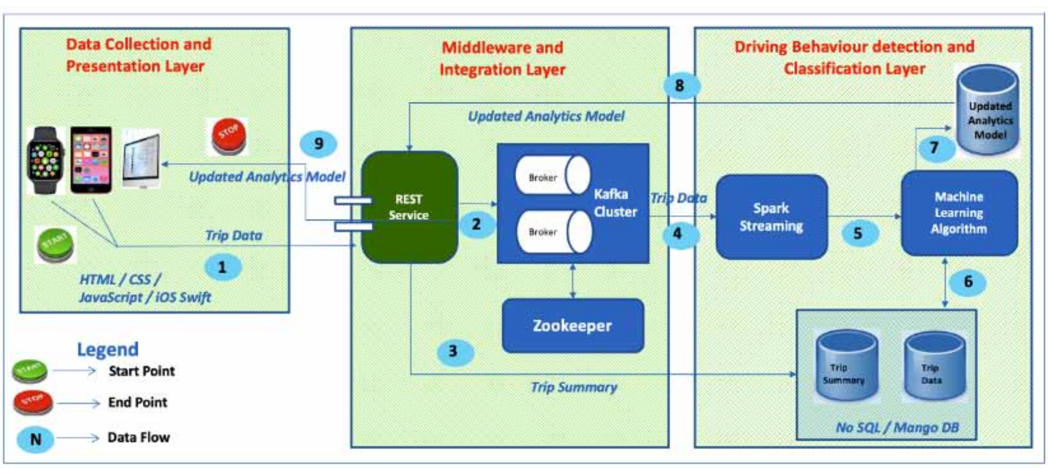
UBI Calculation Engine

This component includes summary and driving behaviour details, start/end time of journey, data/time and location of abnormal driving behaviour of all drivers. The data summary is published and is readily available to insurance companies to calculate the personalized premium based on driving behaviour.

Implementation of RAD

This section presents a detailed description of the implementation of each component of the proposed RAD system, with illustrations. Each component is designed to have an individualized architecture and functionality, so that it can be easily adapted to the specific needs of the different applications.

**Figure 6.
Data Flow Architecture**



Real-Time Driving Data Collection

The proposed system supports real-time data collection in three modes such as black box, OBD II Dongle and smartphone, the characteristics of which are shown in Figure 7. However, due to the merits of smartphone-based data collection such as convenience, flexibility and cost-effectiveness, the system employs smartphone-based data collection, either with built-in sensors or Global Positioning System (GPS). The merits and limitations of these approaches are summarized in Table 1. As hard-cornering events are vital in the identification of road rage/aggressive drivers, this research employs the smartphone GPS for real-time data collection.

GPS is a satellite navigation system that emits continuous navigation signals and data, which allows GPS receivers to calculate location, elevation, velocity and time. GPS signals include longitude, latitude, speed, altitude, course and current timestamp. In RAD, an iOS-based app (front end) is developed to collect the driving data from GPS signals and wearable devices. Hard acceleration, hard braking, hard cornering and speeding events are detected based on the GPS signals and explained in detail in section IV. Further, heart rate is captured with a wearable device.

Data Preprocessing

RAD preprocesses the GPS data to eliminate the noise and to consider only the remaining data for further processing. The following are the preprocessing procedures used by the proposed system:

- All the signals will be passed through preprocessing module/component for normalization.
- In case the data collection devices receive multiple GPS signals in a second, the last signal will be considered.
- Event monitoring is considered for only one minute after the start of the trip (since the frequency of initial GPS readings is not consistent and takes a few samples to calibrate).
- Missing data is replaced with the most frequent values.

Data Format

In RAD, GPS data comprises summary and trail details for each driver, with a unique identifier for driver identification as shown in Table 2. A service is developed to fetch the source address

Figure 7.
Devices for Data Collection

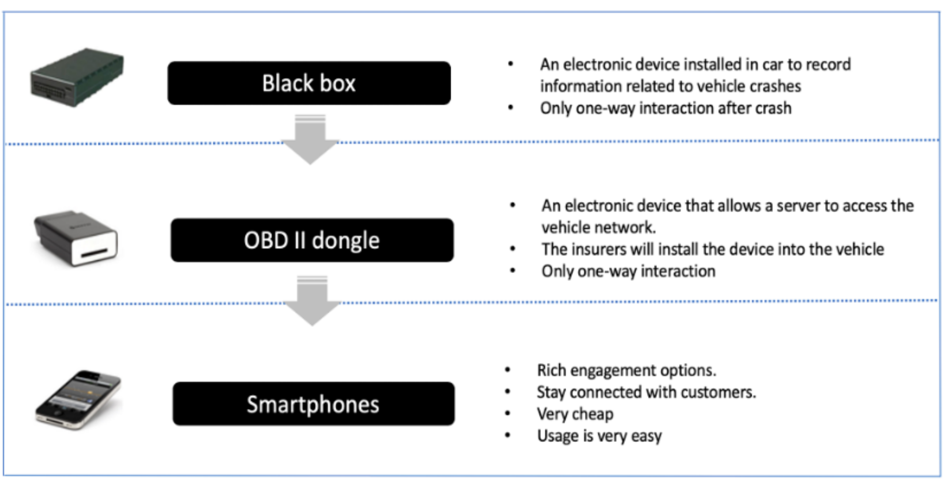


Table 1.
Comparison of Built-In Sensors and GPS

Built-In Sensors	GPS
Advantage	
Less cost and less complexity of implementation to obtain the behavioural events such as hard acceleration and hard braking.	Possibility of unstable location of smartphones and identification of hard-cornering events.
Drawback	
Maintenance of stable position for the smartphones and identifying the hard-cornering event.	Complex implementation and high cost of computation.

and destination address based on the source latitude/longitude and destination latitude/longitude. Likewise, whenever the driver is driving, the app will receive different latitude and longitude points almost every second. For each trip, one summary of information and multiple GPS trails based on the duration of travel are recorded, and are available for the corresponding driver.

Rage and Aggression Detection

This function requires analysis of real-time driving data to identify events such as hard acceleration, hard braking and hard cornering, and speeding incidents. The GPS data are pre-processed and the data-flow depicted in Figure 8 is followed to detect the events. Heart rate is captured from a wearable device and processed as-is. The generation of events and representation of data are presented in Figure 9 with illustrations.

1. **Hard acceleration:** Hard acceleration is a driver event when more force than normal is applied to the vehicle's accelerator, causing the vehicle to cross the permissible acceleration threshold. It is defined as the difference between the final and initial speeds over a period of time as in equation (5). A positive value of this computation signifies hard acceleration:

$$Hard\ \ Acceleration = \frac{\left(Final\ \ Speed - Initial\ \ Speed\right)}{\left(Final\ \ Time - Initial\ \ Time\right)} \tag{5}$$

2. **Hard Braking:** Hard braking is a driver event when more force than normal is applied to the vehicle's brake, causing the car to slow down more quickly than it would under normal driving conditions. It is generally considered to be a warning sign of potential aggressive driving behaviour, resulting in damages to the car and affecting the safety of the passengers. Hard braking is identified by speed changes over a time interval as in equation (6). Negative values indicate a deceleration and the absolute value is used to detect hard braking, compared with a threshold:

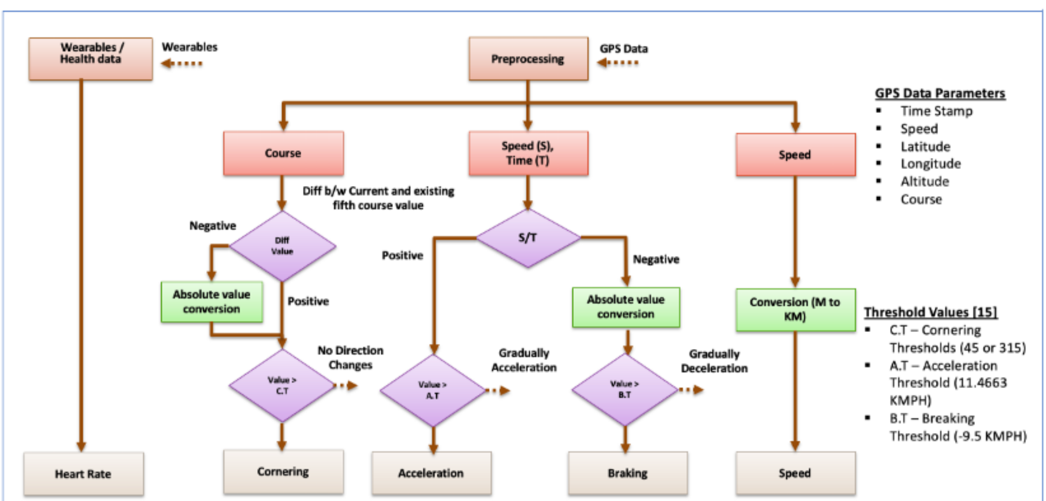
$$Hard\ \ Braking = \frac{\left(Final\ \ Speed - Initial\ \ Speed\right)}{\left(Final\ \ Time - Initial\ \ Time\right)} \tag{6}$$

3. **Speeding Incidents:** A vehicle speeding over the limit can result in a number of incidents such as injuries, property damage, accidents and fatalities. GPS data can be used to create the ideal vehicle speed profile and flag a vehicle as a potential speed violator. GPS systems in vehicles can

Table 2.
GPS Data Structure

Details	Code	Description	Example
Summary	ID	Driver identification number	driverId: 1 duration: 4824, sourceLatitude: 12.922565069610586, sourceLongitude: 80.15254106646069, distance: 21.31363644561462, source: {5, Chinmaya Colony, Sembakkam, Chennai, Tamil Nadu 600073, India.} destination: {Plot No. 1/G1, SIPCOT IT Park, Siruseri, Tamil Nadu 603103, India.} destinationLatitude: 12.831494314490886, destinationLongitude: 80.2161747053472, speed: 9.11578005354186
	ST	Start time of journey	
	Dur	Duration of journey	
	TD	Total distance travelled	
	AS	Average speed	
	Slat	Source latitude	
	SLon	Source longitude	
	DLat	Destination latitude	
	DLon	Destination longitude	
	SA	Starting point address	
	EA	Ending point address	
GPS Trail	CD	Current date and time	date: 24 May 2019 at 9:29:42 AM, longitude: 80.16169384975073, latitude: 12.922921819504342, speed: 11.784402465820312, altitude: 18.870113486413672, course: 111.660834136339
	CLat	Current latitude	
	CLon	Current longitude	
	CS	Current speed	
	Alt	Altitude	
	Cor	Course value	

Figure 8.
Event Analysis



be used to gather data on speeding incidents including speed, time, location, date, etc. Further, these incidents can be aggregated to create a database of speeding incidents for analysis and to identify potential hotspots.

4. **Hard cornering:** Hard cornering occurs when a driver accelerates or decelerates suddenly in a lane, turning a corner at high speed or drifting on the road. Lateral acceleration is an important indicator to identify harsh cornering events, expressed as in equation (7) where V and R are the velocity and the radius, respectively. Cornering events will be detected when this value exceeds 21.6 KMPH:

$$Lateral\ Acceleration = 2 * \frac{V}{R} \tag{7}$$

5. **Heart Rate Monitoring:** Several studies have shown that heart-related events in drivers are associated with an increased risk of accidents, due to a sudden heart attack or arrhythmia, causing the driver to lose control of the vehicle, and often leading to a fatal outcome (D'Allegro, 2017). Further, diabetic events are also found to increase the risk of accidents, as Type 2 diabetes reduces the heart rate. The need for monitoring Heart Rate Variability (HRV) has been advocated in the works of Zheng et al. (2020) and Minea et al. (2021) for a better understanding of how it can be used as an early warning system for detection of high-risk driving behaviour. Hence, in the proposed system, heart rate is being monitored along with driving parameters.

Figure 9d shows the data collected from one driver. The x-axis is the GPS data count, and the Y axis is the heart rate (beats per second). For this driver, the heartbeat ranges from 60 to 100 beats per second. This helps to identify and detect road rage and aggressive drivers.

6. **Driver Data Format:** The GPS data including speed, latitude, longitude, altitude, course and timestamp are received through GPS signals and the heart rate is captured with the wearable device. From this data and the predefined threshold values, the parameter values are derived for cornering, acceleration, braking, speeding and heart-related events. These parameters for driving

Figure 9.
Parameter Analysis a) Acceleration b) Braking c) Speed d) Heart Rate

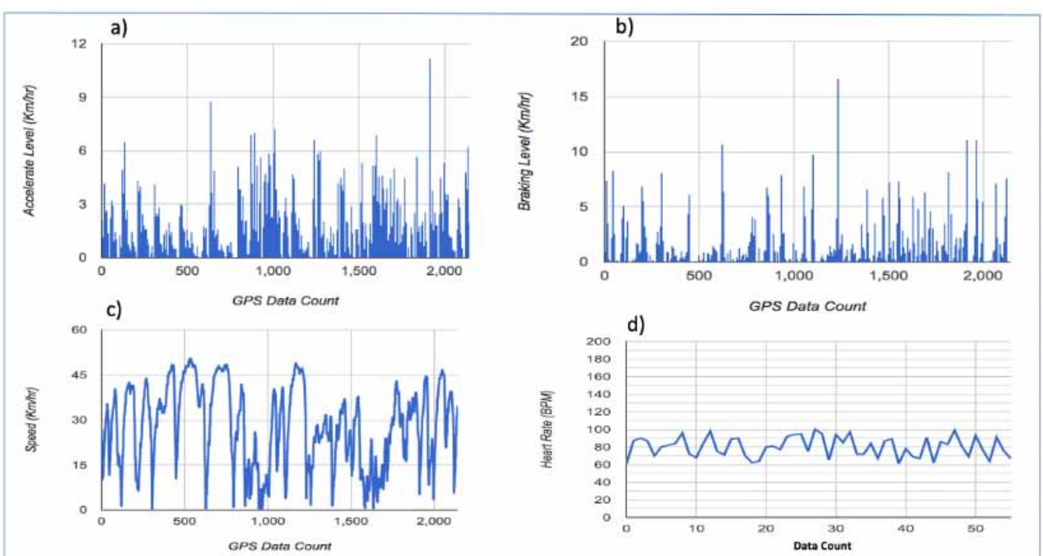


Figure 10.
Event Analysis Parameters a) Acceleration b) Braking c) Speed d) Heart Rate

driver_id	acceleration	brake	corner	speed	heart_rate
1	0.734846	0.521146	4.506803	19.107494	81.914966
3	0.890474	0.846525	4.363857	27.665739	82.827168
1	0.851144	0.335677	4.449883	16.712226	82.681235
3	1.015267	0.854657	4.519219	27.126673	83.270846
1	0.864894	0.414640	4.473174	15.451233	82.669037
3	0.959536	0.777570	4.491046	31.453006	82.532640
1	0.759775	0.719642	4.465000	29.084302	82.460000
1	0.666067	0.398067	4.462609	23.035318	82.888261
3	0.930770	0.843347	4.395122	27.637526	82.703049
1	0.591245	0.376486	4.380074	25.458815	82.191882

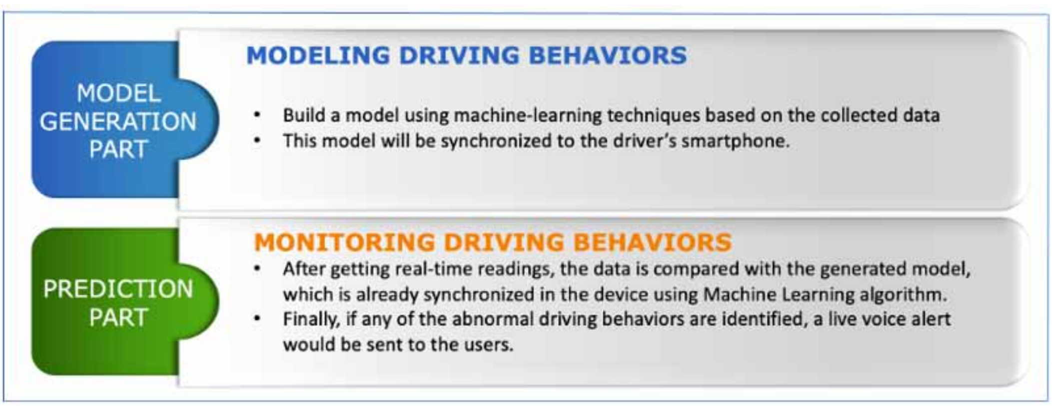
instances of two drivers are shown in Figure 10 with driver_id #1 and driver_id #3. It is seen that for the same driver, the parameters are different across instances.

Driving Behaviour Detection

The mechanism for driving behaviour classification is presented in this section. It comprises the following two phases:

1. **Feature Selection:** During feature selection, raw GPS data and heart rate are analysed to remove redundant and irrelevant features, and the parameters for detection of events with respect to acceleration (A), braking (B), cornering (C), speed (S) and heart rate (H) are derived from the raw data. Several analyses with real-time data revealed that the drivers exhibit unique patterns with respect to these parameters in different instances. From the insights obtained with the analyses, it is evident that all the raw data is correlated with the driving behaviours, and the derived parameters are therefore representative of the driver's actions. Hence, the feature set for training and testing the RAD model comprises the A, B, C, S and H parameters.
2. **Rage/Aggression Detection:** The mechanism for aggression detection is presented in this section. It comprises model generation and prediction as illustrated with Figure 11.

Figure 11.
Two Sub Phases of Rage/Aggression Phase



Model Generation – Modelling Driving Behaviours Using Core ML

The proposed RAD system detects rage/aggressive driving with a machine-learning model. Initially, the model is trained by supervised learning with the feature set comprising the derived parameters under fivefold cross-validation. The classifier is trained to learn driver behaviours from the feature set and to assign one of the target labels—*good, unhealthy* (UH), *road rage* (RAD) and *always bad*—to the data sample. The performance of the model is evaluated with the validation dataset under each iteration, until the model converges to an accuracy of 99%. The algorithm for model generation is given in Table 3 and illustrated with Figure 12.

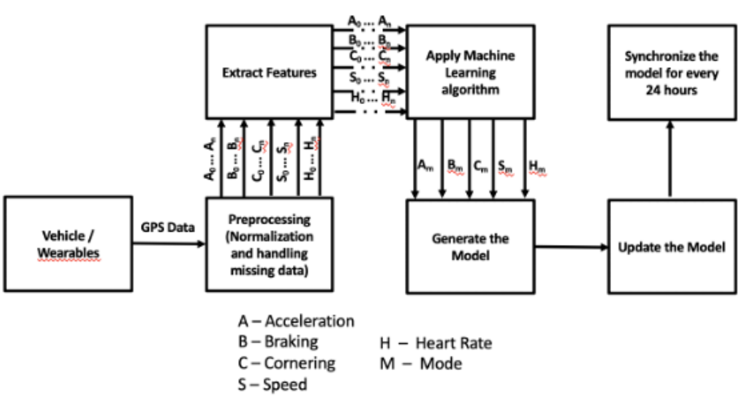
RAD is implemented as a cloud service because the infrastructure of the system is designed and implemented within the cloud so that the data collection and driving behaviours can be conducted in the cloud. However, it is known that driving alerts are safety-critical and their application may suffer from the network delay. So, for quick inferences from real-time data, the model is implemented with On-Device ML. On-Device ML is a popular framework, with APIs designed to support various machine-learning tasks on the device itself. On-Device ML is optimized for on-device performance,

Table 3.
Model Generation Algorithm

Algorithm: Offline Part – Modelling Driving Behaviour

Input: (1) GPS; (2) Wearable Device (WD)
Output: (1) Model (MD)
// Retrieve the driving data from GPS signals
Driving dr ¬ Retrieve (GPS)
// Retrieve the heart rate from wearables
Driving hr ¬ Retrieve (WD)
// Merge the driving and wearables data
Driving data ¬ Merge (dr, hr)
// Preprocessing algorithm to eliminate the noisy data
Driving data ¬ Preprocess (data)
// Generate the model
Model MD ¬ Generate (data)
// Update the model in the device
Update (MD)
// Synchronize the model for every 24 hours
Synchronize (MD)

Figure 12.
Model Generation



which minimizes memory and power consumption. Running strictly on the device ensures the privacy of user data and guarantees that the local app remains functional and responsive when a network connection is unavailable. For every 24 hours, RAD uses On-Device ML to share the generated model with the driver's device.

Prediction – Driving Behaviour Detection

Prediction refers to testing the model with an arbitrary dataset of features captured from a different set of drivers considered for training the model. The A, B, C, S and H parameters derived from the drivers' data are fed as input into the trained model. Based on prior training, the model computes the classification score and assigns the target label to the data sample. When the target class is RAD or UH, live voice alerts are sent to the concerned drivers.

Initially, RAD determines the trip duration by recognizing the beginning and the end of the driving events. Once the driver starts the vehicle, RAD receives the GPS data for every one second. From analysing the traces collected in real driving environments, GPS data is grouped as a single frame for every five seconds. RAD keeps computing the average within the single frame and compares the values with the generated model to classify the driving behaviour as shown in Table 4. This process is repeated until the trip ends. The process is illustrated with Figure 13.

UBI Calculation

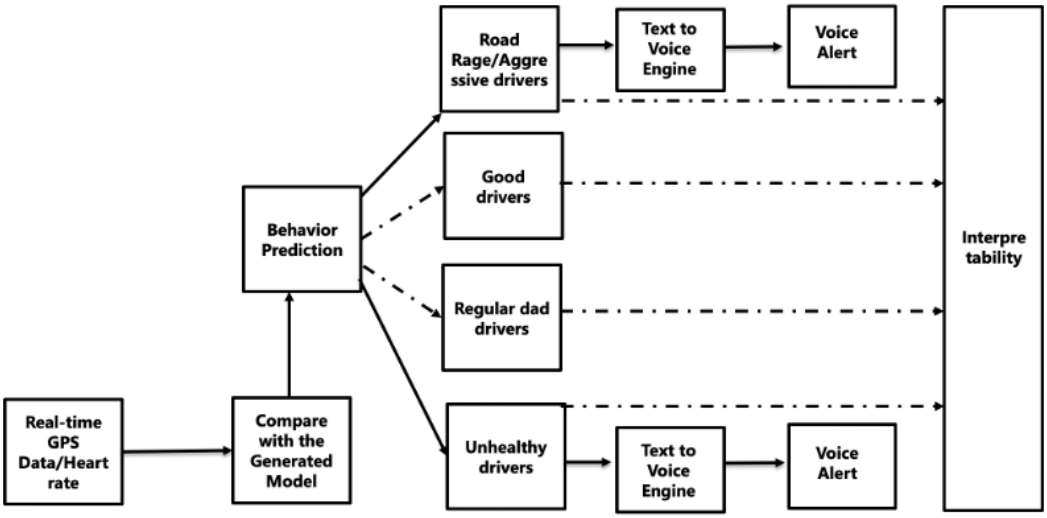
The UBI calculation engine is fed with the classifier decision, derived parameter values and classification scores from the interpretable engine for premium computation. The proposed RAD framework provides freedom for insurance companies to define their own UBI calculation engines based on the policy, driving data and in-house risk assessment. This framework provides well-defined user interfaces and reporting mechanisms to collect user data and present trip summaries and details to the driver, policymakers, law and enforcement authorities, etc.

An illustration of trip details given with Figure 14 shows two driver instances covered by an insurance company. It is seen that the trip attributes and graphical view can be accessed instantly for premium calculation. Multiple views of this data can be presented to enforce access control.

Table 4.
Prediction Algorithm

Algorithm: Online Part – Monitoring Driving Behaviour
Input: (1) Trip Data (TD); (2) Model (MD) **Output:** (1) Driver Classification (dc) 1: // Split the trip data into segments 2: Segment Seq ¬ Retrieve (TP) 3: // Predict the driving behaviour 4: Behaviour beh ¬ Predict (Seq, MD) 5: if (beh is RAD or UH) then 6: { 7: // Retrieve the alert message 8: Alert alt ¬ Retrieve (beh) 9: // Convert the text message into voice 10: Voice msg ¬ TextToVoiceEngine (alt) 11: // Alert the user 12: VoiceAlert(msg) 13: } 14: // Return the classification of driver 15: Output dc as driving behaviour classification 16: dc¬beh

Figure 13.
Driving Behaviour Prediction



Generally, insurance companies use enterprise servers to run UBI calculation engines in order to log the trips, manage people, raise alerts, schedule activities, implement premium rate changes, etc. As part of this research, a web portal is implemented with HTML 5.0 and CSS 3 for monitoring the drivers in real time, raising warnings, UBI calculation, analysis, etc. Driver classification over a small population grid can be visualized in real time as in Figure 15.

Further, the portal also provides localization of aggressive driving with Google Maps as shown in Figure 16. On detection of aggressive driving near Nanmangalam forest, Chennai on June 1, 2018 at 8:55:07 AM, the voice alert was given by the RAD system installed on the driver's smartphone, and the map was rendered. This feature allows policymakers to investigate the driving patterns in different geographical areas, identify the frequent locations of aggressive driving and decide on the type of driving insurance to be introduced.

EXPERIMENTAL RESULTS AND DISCUSSIONS

This section presents the experimental setup for training and testing the models, empirical evaluations, performance and interpretability analyses in the following subsections.

Figure 14.
Trip Details

ROAD RAGE AND AGGRESSIVE DRIVING

28-Jul-2022 (Thu)

Trip Id	Source	Destination	Start Time	Duration	Distance	Travelled Route	Graphical View
1591425132648	183,Velachery Main Rd,Gowriwakkam,Sembakkam,Chennai,Tamil Nadu 600073,India	1,1st Street,Rajarajeshwari Nagar,Chitlapakkam,Chennai,Tamil Nadu 600073,India	11:38:49	23 min,23 sec	3.8 KM	View	Click Here
1591422034916	Mohan Pizza,Chitlapakkam Main Rd,Maruthi Nagar,Chitlapak9kam,Chennai,Tamil Nadu 600064,India	165, Velachery Main Rd,Ammai Theresa Nagar,Tambaram East,Tambaram,Chennai,Tamil Nadu 600059,India	11:04:32	6 min,1 sec	2.3 KM	View	Click Here

Figure 15. Visualization of Driver Classification

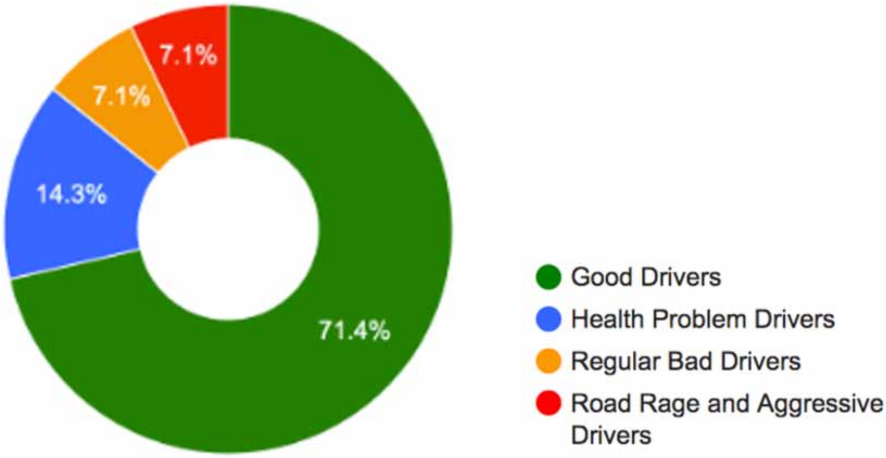


Figure 16.
Rage/Aggressive Driver Detection and Localization

Table 5.
Trip Count

Trip Count (Before)			Trip Count (After)		
Description	Count	%	Description	Count	%
Total	1761	-	Total	1649	100
Proper	1570	89.15	Proper	1649	100
Missing	79	4.49	Missing	-	-
Invalid	112	6.36	Invalid	-	-

Table 6.
Missing Values

ID	Acceleration	Brake	Corner	Speed	Heart Rate
2	0.202907	0.554879	3.888889	26.397901	-
3	-	0.188367	4.507761	23.320976	83.290466
3	0.326750	-	4.525773	24.752134	82.943299
1	0.614350	0.555239	-	20.321107	82.651543

Dataset and Experimental Setup

The proposed model is trained and tested with real-time data collected from twenty drivers from different vehicles. The data is collected from drivers living in different communities following various commute routes for daily driving activities that include commuting to work, shopping and so on. On average, each driver may drive 20 to 40 kilometres per day and the driving data is collected for a period of 24 months including hard acceleration, hard braking, speeding incidents, hard cornering and heart rate from all the drivers, for identifying road rage and aggressive driving using smartphones. In total, the RAD dataset consists of 1761 trips as shown in Table 5. Out of 1761 trips, 1570 trips (89.15%) are proper, 112 trips (6.36%) are invalid and 79 trips (4.49%) have a few missing columns as shown in Table 6. In the dataset, the missing columns are replaced with the most frequent values, ignoring the invalid trips. In this research three discrete models are employed in RAD, which are trained and tested with the valid data subsets as shown in Table 7.

Performance Evaluation

The performance of the RAD model is evaluated with accuracy, precision, recall and F1 metrics from the True Positive (TP), False Positive (FP), True Negative and False Negative (FN) values obtained on the classification of test data. Accuracy is a measure of the number of correct classifications expressed as in (8):

$$Accuracy = \frac{\left(TP + TN\right)}{\left(TP + TN + FP + FN\right)} \tag{8}$$

Sensitivity or recall is the number of correctly identified positive samples out of the total number of positive samples as given in (9):

Table 7.
Training and Testing Data Description

Category	No. of Trips	
	Training	Testing
Good	752	188
Unhealthy	246	62
Road Rage	132	33
Always Bad	189	47
Total	**1319**	**330**

Figure 17.
Confusion Matrices for Rage/Aggressive Driver Detection

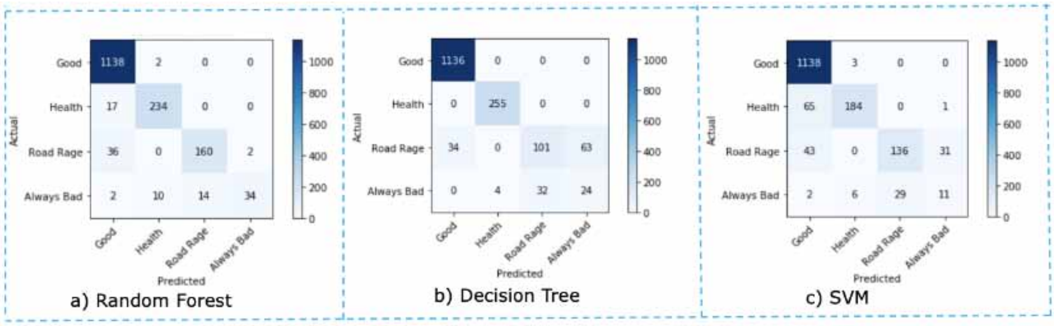


Table 8.
Classification Performance Metrics

Behavior	Precision (%)			Recall (%)			F1 Score (%)			Overall Accuracy %		
	RF	DT	SVM	RF	DT	SVM	RF	DT	SVM	RF	DT	SVM
Good Driver	99	99	99	100	100	100	99	99	100	98	96	93
Health Issue Driver	100	98	96	94	94	96	97	96	96			
Road Rage Driver	100	96	92	100	100	100	100	98	96			
Always Bad Driver	100	100	100	100	90	65	100	95	76			

$$Sensitivity = \frac{TP}{\left(TP + FN\right)} \tag{9}$$

Precision refers to the number of correctly identified positive samples out of the total number of positive samples predicted by the model as in equation (10):

$$Precision = \frac{TP}{\left(TP + FP\right)} \tag{10}$$

F1 score is the harmonic mean of precision and recall expressed as in (11). It is used as a reliable measure to evaluate the models trained with unbalanced datasets. The F1 score is more robust to the imbalance in the training data than accuracy, precision or recall, as the harmonic mean is used to balance the contribution of precision and recall, which prevents the metric from being overly influenced by either of them:

$$F1 = 2^{*}\frac{Precision^{*}Recall}{Precision + Recall} \tag{11}$$

The metrics evaluate in [0 1], signifying best classification performance when the values are closer to 1. The DT, RF and SVM classifiers are trained and tested with the dataset described in the previous section. The performance metrics evaluated for four-class classification are shown in Table 8.

Further, the classification results are visualized with the confusion matrices, which depict the correct classifications and misclassifications under each category. The confusion matrices for the three classifier models are shown in Figure 17.

It is seen that best overall classification accuracy is achieved with the RF model, which exhibits a smaller number of misclassifications compared to DT and SVM. While the number of misclassifications is 3 for RF, the DT and SVM models make 5 and 9 wrong predictions, respectively. A closer observation of the results shows that a greater number of erroneous predictions are evidenced from the *good* to *unhealthy* categories, viz. 2, 3 and 6 for RF, DT and SVM classifiers. Further, it is seen that all the data samples under the *unhealthy* category are correctly classified by the three models. Further, *road rage* cases are also identified perfectly by RF and DT, and 1 misclassification is evidenced with SVM. This result shows that the models are sufficiently trained to discern the driver categories. However, the highest number of misclassifications from the *good* to *unhealthy* categories in each model signifies more FPs that must be eliminated.

Explainable Analysis

Conventional machine-learning models are seen as black box models, the predictions of which are not easily interpretable (Alwosheel et al., 2021). In order to understand how a machine-learning model works and to identify which factors influence the predictions, it is often necessary to interpret the model behaviour. Explainable analysis facilitates such interpretations by enabling the user to understand the input features that the machine-learning model uses to make the predictions. Explainable analysis is significant in the context of this research, as the insurance companies need to provide a user with an intuitive explanation of the factors that lead to driver categorization, to establish trust. Further, this analysis also helps to identify and eliminate trivial features, and debug and optimize the model. Two significant works on explainable analysis with respect to travel domain are presented by Alwosheel (2020) and Barbado and Corcho (2021).

The explainable analysis pipeline for RAD detection is shown in Figure 18. This analysis is performed with the DT, RF and SVM classifiers employed in this research to analyse their behaviour with respect to input features. This analysis presents insights on which of the derived parameters influence the classifiers' decisions and also helps to guide the drivers towards modifying their behaviour to minimize their risk of being classified as aggressive.

Interpretable machine-learning models possess one or more of the following features for analysing their behaviour. In this context, the capabilities of the RAD model are illustrated with Figure 19.

- **Text explanation:** Ability to generate textual explanations from the model predictions.
- **Visual explanation:** Ability to provide visual interpretation of model behaviours for post-hoc analysis.
- **Local explanation:** Ability to segment complex solution spaces into smaller subspaces and provide explanations in terms of solutions to less complex problems.
- **Explanations by example:** Ability to extract data samples related to the result to understand the whole model.
- **Explanations by simplification:** Ability to build a whole new system posing less complexity from the trained model.
- **Feature relevance:** Ability to clarify the inner functioning of a model by computing a relevance score for its managed variables for post-hoc analysis.

The interpretable analysis for four driving instances is given in Table 9. The class score for each target class is given with values of the derived parameters. It is seen that driver #9 is classified *always*

Figure 18.
Interpretable Machine-Learning Model

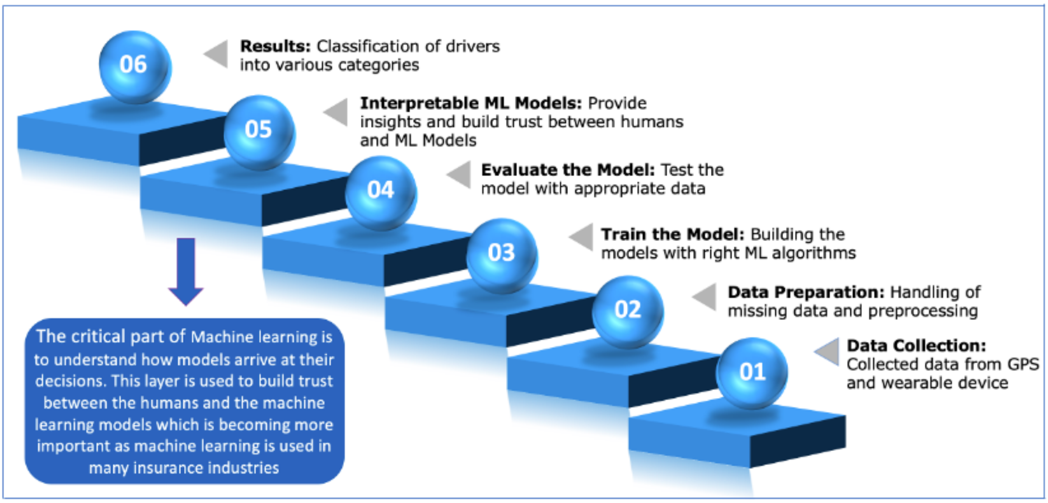


Figure 19.
Interpretability

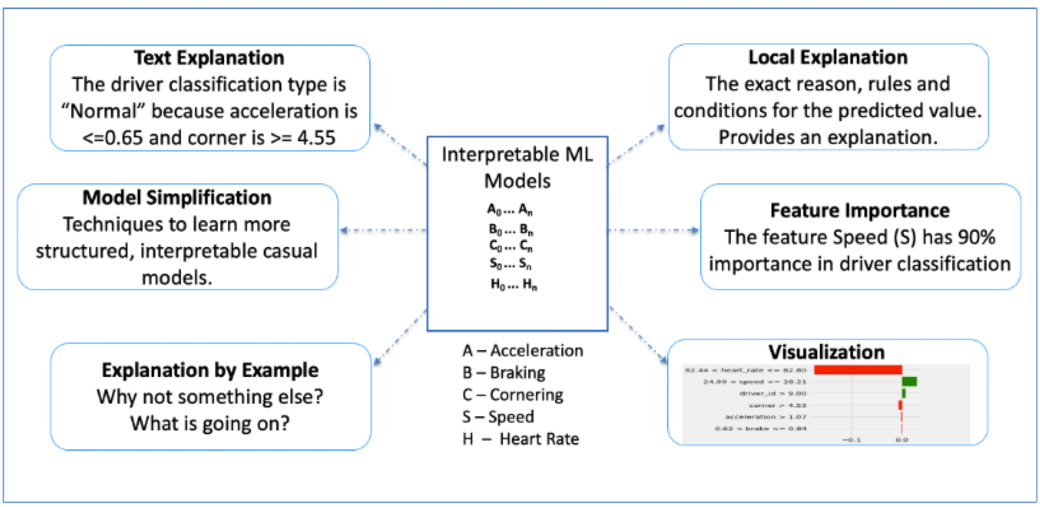


Table 9.
Interpretability Analysis

Driver Classification Type	ID	Driver Classification Prediction Probabilities				Driver Classification Parameter Values				
	Driver ID	Normal	Health	Road Rage	Always	Acceleration	Braking	Cornering	Speed	Heart Rate
Normal	1	**0.98**	0.02	0	0	0.81	0.57	4.45	20.56	82.54
Health	10	0.03	**0.95**	0	0.02	0.74	0.64	4.62	27.02	83.54
Road Rage	5	0.03	0.01	**0.95**	0.01	0.71	0.62	4.60	32.71	82.04
Always	9	0	0.05	0.12	**0.83**	0.81	0.58	4.45	37.68	83.68

bad with respect to B, S and H parameters. This analysis alerts the driver to correct the braking and speeding activities and take care of their health.

Further, local explanations for the four classes of drivers are shown in Figure 20. The ideal values of the parameters is given for each class for a clear understanding of the driving behaviours in real time. Visualizing these parameters on the dashboard can help the driver to control the driving behaviour to avoid adverse outcomes.

Comparative Analysis and Discussions

Experimental results show that the proposed RAD system exhibits best classification accuracy with the test dataset. Since the existing models are trained with different datasets, the RAD system cannot be compared with them based on quantitative metrics alone. For a fair comparison, a comparative analysis with the state-of-the-art systems is presented in Table 10, highlighting the merits and limitations of these systems.

This analysis shows that the proposed RAD system is unique among its kind for aggressive driving detection for personalized insurance computation that considers behavioural, environmental, physiological and emotional factors. The proposed RAD system has a distinct edge over other systems as it considers the various parameters that affect the decision making process, enabling insurance companies to identify high-risk drivers at an early stage to avoid accidents. The alert mechanisms incorporated into the system can further reduce risk-proneness, as the system is implemented in the cloud, raising the possibilities of real-time monitoring and preventive measures.

Further, unlike other systems, the proposed model does not use the raw data captured directly from sensors. The DT, RF and SVM classifiers are trained with features characterising adverse driving events, derived from raw data and heart rate, resulting in a highest classification accuracy of 98% for the RF classifier. This result is indicative of the fact that the RF classifier is able to learn the complex patterns associated with the driving behaviour data and can be effectively used for the detection of rage/aggressive driving. Basically, RF poses some advantages such as flexibility, minimized overfitting, fast learning and ability to capture the nonlinear patterns in the data compared to other machine-learning models. Further, the RF-based rage/aggressive driver detection model shows good

Figure 20.
Interpretable Machine-Learning Model – Local Explanation

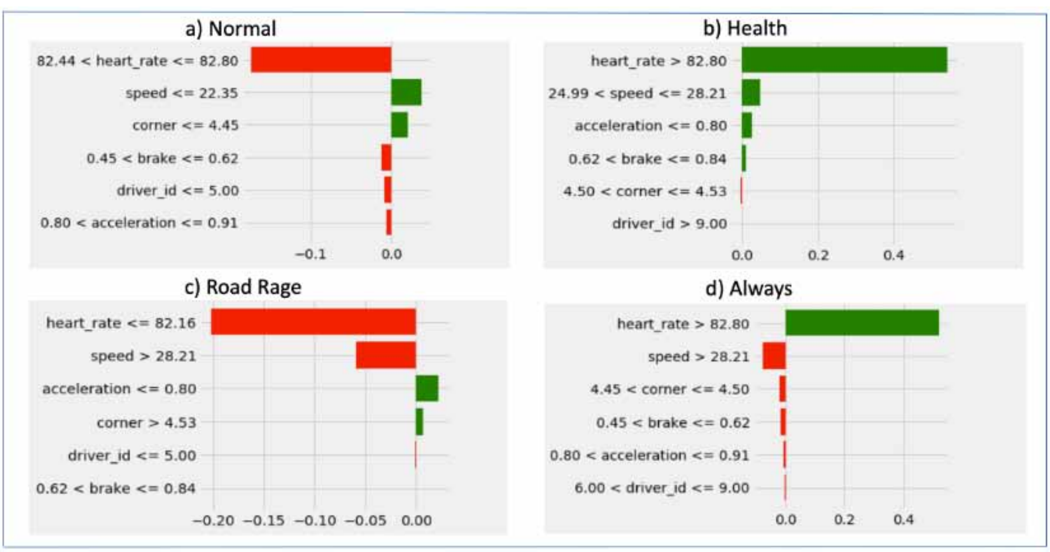


Table 10.
Comparative Analysis with State-of-the-Art

Ref No. (Year)	Detection Model	Model Description	Classifications	Performance Metrics	Advantages	Limitations
(Yu et. al., 2016)	D^3	Fine-grained classification of four abnormal driving behaviours is performed with SVM and NN classifiers.	Fast U-turn, sideslipping, sudden braking, weaving, swerving, and turning with a wide radius	Accuracy - 95.36% (SVM) Accuracy - 96.88% (NN)	Models are trained with features extracted from 6-month driving traces collected from real driving environments.	152 features are used in training. The system is available only for Android version.
(Zhang et al., 2017)	SafeDrive	Online unsupervised and status-aware approach to detect abnormal driving behaviours from large-scale vehicle data using state graph (SG) to detect seven anomalies.	Rapid acceleration, sudden braking, over speed, rapid swerving and neutral taxiing	Accuracy - 93%	Does not require labelled data.	Environmental and behavioural factors are not considered.
(Shi et al., 2015)	Personalized Driving Model	Personalized models are constructed for each driver based on vehicle and road condition. Driving styles are quantized from ESD analysis.	Abnormal and steering abnormal rates	AR-106 SAR-32	Suitable for drunken driving detection, vehicle calibration and intelligent transport systems.	Raw vehicle data is not sufficient for evaluation.
(Liu et al., 2017)	DSAE-based visualization model	Deep Sparse autoencoder (DSAE) is used to extract hidden features for visualization of driving behaviour. Visualization method called a driving colour map maps the extracted features to the RGB space.	Simple behaviours: High speed, forward stopping, right rear reversing and left rear reversing	Average F Score for modelling complex driving behaviours - 0.626	Models simple and complex driving behaviours. Supports numerical evaluation of visualization with SVM classifier.	Visualization result can yield different visualization results for the same data due to rotational degree of freedom between feature spaces.
(Daptardar et al., 2015)	HMM and Jerk Energy-based model	HMM are used to detect lateral manoeuvres and Jerk Energy-based technique to detect longitudinal manoeuvres	Turns, lane changes, hard accelerations and hard braking	95% accuracy (Event Detection) 90% accuracy (Driver Profiling)	Detection of lateral and longitudinal manoeuvres.	Complex events and profiles are not modelled.
(Yin & Chen, 2018)	Multiple kernel learning model	An integral model is trained on vehicle, driver and lane attributes with Adaboost algorithm for three-level risk classification.	High, middle and low level risks	Varies between 20% - 100% with number of kernels	Accuracy of risk assessment increases with multiple-type attributes.	Accuracy of risk assessment is not expressed quantitatively.
(Arun Kumar & Yellampalli, 2018)	Black box	Binary logistic regression model for binary risk classification.	Risk and NoRisk	Accuracy - 51%	Logistic regression is simple and fast.	Low prediction accuracy.
(Brahim et al., 2022)	GBDT LSTM	Six discrete models are trained on data fused from multiple sensors in smartphone for four risk levels.	Intermediate, aggressive, dangerous and normal	Accuracy: CatBoost - 80% XGBoost - 82% LightGBM - 88% LSTM - 70% LSTM-CNN - 76% LSTM-FCN - 79%	Fusion of data results in better classification accuracies.	The models are trained and tested on simulated data.
RAD (Proposed)	DT RF SVM	Three models are trained discretely to classify drivers into four classes.	Good Unhealthy Road rage Always bad	Accuracy: DT – 96% RF – 98% SVM – 93%	Behavioural, environmental, physiological and emotional factors are considered. Explainability Analysis is provided to understand the behaviour of the model.	Driving data is collected from a cohort.

generalization performance on unseen data due to its ability to randomly select a subset of features at each iteration during the learning process. The machine-learning models can be tuned to specifically detect the behaviour that is of interest, and this can lead to better detection performance.

However, certain limitations of the proposed RAD system listed below must be addressed in future:

1. Aggressive driving behaviour is a complex phenomenon that requires extensive behavioural, environmental, physiological and emotional factors to be considered. These factors are often dynamic and are not always consistent. Thus, the proposed model is not a complete and robust system, but can be used as a preliminary tool for proactive driver risk assessment. This drawback can be overcome by training the models with grid-wide data, considering the changes in factors and driving behaviours over time.
2. The dataset used in this paper is obtained from a single cohort in India. The accuracy of the dataset might be different in other countries and cultures. For this reason, the model developed in this paper should be validated with datasets from other sources.

CONCLUSION

The objective of this research is to deploy an automated system for detection of aggressive driving behaviour using a machine-learning model capable of detecting driving behaviours at four levels of aggressiveness—namely, *good, unhealthy, road rage* and *always bad.* The proposed RAD system features an integral framework comprising a classifier model, interpretability engine and alerting mechanism. The classifier model is trained with behavioural, environmental, physiological and emotional factors, facilitating differential profiling and personalization of the driving behaviour, essential for risk-based insurance pricing. The proposed system is tested with DT, RF and SVM models demonstrating the best classification accuracy of 98% for the RF classifier.

The proposed system can be extended to accommodate the dynamics in telematics data, sensor capabilities and evolving smartphone technologies in detecting the driving behaviours. Particularly, the effects of pandemics are highly pronounced in road safety due to stringent regulations imposed by governments, changing the mobility frequencies and commuting distances of road users. The traffic data captured is minimum, when the travel restrictions are in place. This scenario makes it difficult for UBI models to assess risks and make inferences on driving behaviours using this data.

The proposed RAD system can be finetuned to accommodate the changing context of road user mobility and behaviours by analysing time-dependent changes in data to enhance insurance pricing and risk management.

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We declare that this manuscript is original, has not been published before and is not currently being considered for publication elsewhere.

CONFLICTS OF INTEREST

The authors declare that they have no conflict of interest.

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