Driver Behavior Monitoring Based on Smartphone Sensor Data and Machine Learning Methods

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Abstract—**This paper aims at investigating the usage of smartphone sensor data and machine learning methods to monitor abnormal driver behavior. For this reason, a literature review was carried out in order to get insights into current studies of this field. Different machine learning approaches as well as different sensor data are used and from the findings of the literature. The neural networks were chosen for the classification task in the proposed for driver decision support system. Furthermore, the proposed methodology utilizes smartphone based sensor data. This way the majority of people can access the system no matter their current car.**

I. Introduction

Driving takes place in everyday life of many people around the globe. Though driving is dangerous and can lead to fatalities. According to statistics of traffic fatalities for 2017 in the United States, a total of 37133 people died in motor vehicle traffic crashes [1]. Furthermore, the last evaluation of the economic costs of the traffic crashes in the United States revealed a staggering annual amount of 242 billion dollars [2]. This data shows room for improving the traffic safety. Furthermore, [3], [4] acknowledge the driving behavior as a critical role for traffic safety. Different behaviors and their respective patterns can lead to accidents. With the increase in available data regarding the driving styles as well as contextual data about the drivers and the trips, conclusions can be made about how the identified driver behavior is related to safe and unsafe driving. Thus, identifying the driving behavior can lead to an increase in overall traffic safety. In order to achieve this goal, the evaluated behavior of the drivers should be used to warn the individual driver about his condition and give reasonable recommendations towards getting in the desired safe way of driving. Recognizing different patterns and classifying data can be implemented using machine learning algorithms.

This paper gives insights into the usages of machine learning approaches in the literature in order to monitor driving behavior and introduces a model with a machine learning approach for the driver behavior identification task. It should be clarified how those approaches are used in previous works and which data they incorporate. In the selection of the found papers, a special emphasis was made concerning the source of their data, in particular the usage of smartphone-embedded sensors. The usage of smartphones is widespread in the society and therefore a reasonable way of gathering information for everybody. This way not only modern cars with build in sensors but also older car models can be supported by the proposed system. The methodology in Section V is based on smartphone sensors and can be incorporated in the existing threshold based driver decision support system described in Section IV.

For this study, the following research questions are considered:

- Which machine learning approaches exist to classify driver behavior?
- Which of those Machine learning approaches are suitable to cluster drivers based on smart phone sensor data?

We identify the scientific novelty of the paper in the following points: (1) comprehensive related work in the area of machine learning application for the driver decision support system, (2) provide answers to research questions that allows to understand how and what machine learning approaches can be used for the driver decision support system, (3) develop the reference model for driver decision support system design based on driving data analysis using the machine learning algorithms.

The following parts of the paper include the Section II where the related work is presented. Section III is dealing with the approach analysis, here are the findings of the literature analysis explained in detail regarding the considered research questions of this paper. Furthermore, relevant information about the different machine learning approaches are provided in this section as well. In Section IV the Driver Decision Support System is explained, which is meant to carry out the proposed approach in the future. The proposed methodology of this paper is presented in Section V, followed by a conclusions presented in Section VI.

II. Related Work

To gather information from relevant sources a literature review was carried out regarding the past and present use of machine learning algorithms for monitoring the driver behavior. Therefore the databases of SCOPUS and ScienceDirect where analyzed with the following search terms queries (see Table I).

Thus the following relevant studies has been identified and briefly covered in this section. In order to cope with the given research questions a special emphasis was made with regards to the used machine learning approaches and the underlying data for the machine learning algorithms.

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TABLE I. SEARCH QUERIES USED FOR PAPER SEARCH

#	Search Query
1	"machine learning" AND ("driving behaviour" or "driving behavior") AND (smartphone OR mobile) AND (safety OR accident)
2	"driver classification" AND (behaviour OR behavior) AND "machine learning"
3	"driver behavior" AND classification AND "machine learning"

Paper [5] considered driver profiling with different Android smartphone sensors like accelerometer, linear acceleration, magnetometer and gyroscope. They implemented the classification with different machine learning algorithms like Artificial Neural Networks, Support Vector Machines, Random Forest, and Bayesian Network in order to assess which sensor/method assembly enables classification with higher performance. The results show that Random Forest performs the best followed by artificial neural networks. Bigger window sizes performing better results and gyroscope and accelerometer are the best sensors for their classification task.

Authors of the paper [4] presented an investigation of driving skills using a machine learning method for classifying driving maneuvers with the overall aim to create a framework to make driving safer. The driver model is trained from sensor data related to the driving environment, vehicle response, and driving behavior for driver. Once the model is trained, the driving skills are classified automatically for novel situations. This paper uses the k-nearest neighbor classifier and Support Vector Machine and take different curve driving scenes as the basis of the classification in order to tag the drivers in different driving skill levels. The collected data include steering angle, speed, longitudinal acceleration, lateral acceleration, yaw rate, accelerator control, brake control, lateral displacement, longitudinal displacement, accelerator control speed, and brake control speed. The results show that SVM performs better then k-NN in this model.

The relationship between driver characteristics and their driving behavior, accidents and ticket rates is presented in paper [6]. As a result a risk index is proposed in order to classify the risky and non-risky drivers. To achieve this 1769 questionnaires were collected to gain information on drivers' personality, age, gender, education, driving behaviors (lapses, errors and violations), accident and ticket rates. The participants were clustered using K-means clustering. It was found that $k = 4$ was the best cluster number for significant differences in the dataset.

Authors of the paper [7] investigated how to make driver distraction state classification more efficient by applying machine learning techniques like SVM and logistic regression to existing datasets. It was furthermore examined how to reduce computation by limiting the input variable cardinality to 2 by taking the 2 most important variables into account. The accuracy of the reduced input variable run was at 74.16% which is just short of the „full“ 16-variable run at 75.38%.

Paper [8] considers possibility to detect and predict an impaired driver state such as drowsiness by developing an Artificial neural network for those tasks. Furthermore, the inputted information to the algorithm is collected from different data sources ranging from physiological, behavioral, to psychological data about the driver, as well as performance information from the vehicle. Different datasets from different datasouces where evaluated in order to determine the most optimal success in detecting and predicting impairment. The data are collected from participants in a driving simulator. The generalisation and inter-individual variability is viewed as a challenging task in order to evaluate drivers whose data is not trained beforehand.

Study [9] aimed at using the multilayer perceptron classifier (deep learning) to detect Drowsiness dangerous state of drivers from various backgrounds in different scenarios such as wearing sunglasses or different lighting levels. The purpose is to design a system which is computationally light in order to use it in mobile devices with their respective limited calculation and storage capacity. The training data is extracted from the National Tsing Hua University Driver Drowsiness Detection Dataset and the proposed model achieves an accuracy rate of 81 %.

Paper [10] proposed a model for detecting sudden braking and aggressive driving behaviors with data collected from smartphone sensors. A dynamic time warping technique is used for classification aiming for mobile devices with constrained resources. The proposed algorithm has an accuracy of 100% for detecting braking events, 97% for detecting left and right turns and 86.67% for detecting aggressive turns.

Authors of the paper [11] proposed a two-stage clustering via K-means in order to cluster driving profiles with regards to safety on a variety of different trips. In the first clustering step aggressive and non-aggressive is distinguished based on harsh events such as acceleration or deceleration, as well as speed and acceleration distributional characteristics. In the second stage of the clustering the variability of driving behavior is investigated through speed violations and usage of mobile phones. As a result different driving states in relation to distraction via smartphone use and risky driving are found. Based on the clustering each trip can assigned to 6 categories of safe driving ranging from safe behavior to aggressive/distracted behavior. The used dataset contains more than 10000 trips from 129 drivers.

Paper [12] proposed a driving style evaluation system called CADSE which is based on data from smartphone sensors. The system is evaluating different driving maneuvers on three successive time frames and additionally takes the context into account such as traffic condition and car sensitivity. The extracted data is classified in the respective subsystem using different machine learning approaches such as decision tree, support vector machine, multi-layer perceptron, naive Bayes classifier, Radial basis function network and k-nearest neighbors, additionally these algorithms are compared against each other to gather the most accurate algorithm for the individual tasks.

Paper [13] proposed a driver performance model where participants take part in a driver-in-the-loop simulator to gather the data about lane keeping and speed violations. The drivers are modelled with both artificial neural network and neuro-fuzzy inference system to compare these algorithms in terms of accuracy. The former approach with artificial neural network proofs to be more accurate in this driver performance model.

Paper [14] proposed a personalized driving state recognition system which takes into account not only personalized driving characteristics but also considers contextual information such as the road type. This leads to an increase in accuracy of the driving state recognition for individual drivers. For the classifier algorithm they compare discriminant analysis, decision tree, k-nearest neighbor, support vector machine and random forest and they found that the latter outperforms the other techniques.

Paper [15] proposed a unified data collection and analysis framework, called DarNet. It utilizes ensembled neural Networks for classification and smartphone sensor based data to detect and classify distracted driving behavior. Furthermore they acknowledge privacy concerns by down sampling collected video-data which still produces a reasonable classification accuracy of 80%.

Authors of the paper [16] investigated the driving behavior with sensor data from smartphones such as accelerometer and gyroscope. The data is classified using Bayesian Networks, random forest and Multi-layer perceptron in aggressive and non-aggressive driving events. The findings recommend both Bayesian algorithms for their great statistical execution and multi-layer perceptron for its fast and intelligent computing.

Paper [17] proposed a fine-grained abnormal driving behavior detection and identification system which make use of smartphone sensors for acceleration and orientation in order to train both a support vector machine and neuron network with empirically grounded data from real driving situations. The identification of abnormal driving events distinguishes between weaving, swerving, sideslipping, fast U-turns, wide-radius turning and sudden breaking. Furthermore they investigate different impacts on the results such as training set size, traffic condition, road type, smartphone placement and the sensors sampling rate.

III. Approach Analysis

This section will cope with the extracted information from the literature in order to deal with the considered research questions. Through the literature analysis 14 related papers were selected which propose the use of machine learning algorithms to detect or to some extend identify the behavior of drivers. The findings of the used machine learning approaches can be found in Table II.

A. Algorithm Explanation

To give the reader a better understanding of the gathered machine learning algorithms a short explanation to them is provided in this subsection.

Support vector machine (SVM) is an algorithm which is used to find a hyperplane in an N-dimensional space, where N refers to the number of features that are used. The hyperplane should separate the data points in a way that the distance between the plane and all data points is maximized so that future data can be reliable distinguished in the appropriate classes. It is used in both regression and classification tasks like K-nearest neighbor (KNN) as well. It needs some pre-labeled data from which it can learn. When an unlabeled data point is fed to the algorithm in order to classify it the K nearest data points depending on a chosen distance metric are evaluated and according to the most shared features it is classified like them. This way based on a chosen K, classes can be distinguished and the data is classified based on a similarity concept.

Neural networks try to mimic the neuronal structure of the human brain with a network of connected neurons, which classifies input data according to weighted interconnections. They consist of an input layer for the data points and various layers of neuron nodes, which lead to a desired output. They can learn with newly presented data and adjust their weight functions accordingly. There are several different approaches to neural networks, for example artifiacial neural networks which are used by [8], [13] or multi layer perceptron classifiers which are used by [9], [12], [13], [16]. Furthermore is the use of convolutional and recurrent neural networks by [15] discussed.

Bayesian networks are probabilistic graphical models to model conditional dependences represented by edges in a directed graph. They are used to represent multivariate probability distributions and usually need some expert knowledge in order to determine the most suitable probabilistic connections between nodes.

A decision tree can be seen as a tree-like graph representation of a decision which contains conditional control statements of various features to find an appropriate outcome or classification of a given data point. As an extension to that concept many random trees can be build which is then classified as random forest algorithms, this is investigated by [5], [14], [16].

The K means algorithm can be viewed as an unsupervised learning method, which takes an unlabeled dataset and tries to find K clusters among them. This is achieved by choosing centroids and assigning the data points to a centroid based on distance and then building new centroids based on the previously build centroid clusters that are a better generalization of the data points that contained the old clusters. Next, each data point gets reevaluated in order to assign them to eventually new and better fitting centroids until the data is well enough grouped in K clusters. Logistic regression models the probabilities for binary classification independent variables.

The dynamic time warping is a time series (sequence of events which happen in an order of the timing of the events) alignment algorithm which aligns two sequences of feature vectors even if they vary in speed. It allows a non-linear mapping of one signal to another by minimizing the distance between the two.

Discriminant analysis is used to reduce the dimensionality of a dataset in supervised classification problems. It is used as a preprocessing step in machine learning to reduce complexity.

B. Sensor and Input Data

To get a better understanding of the used input data to the different machine learning approaches and to cope with the second research question the Table III relates the applied machine learning algorithms in the selected papers with their input data. All papers except [6] as well as [13]. proposed systems utilizing smartphone sensor data – even if they don't propose a smartphone based system some of their measurements can be done with smartphone based sensors as well.

These smartphone sensors include accelerometer, gyroscope, magnetometer, gravity sensor, orientation sensor, GPS, camera and calculated measurements like gravity and driving time. The driver based category is divided into driver information and driver measures, the former covers personal traits, gender, age, education, violations, ticket rate, accident rate, score on circadian typology, score on Epworth scale, sleep quality, driving frequency and numbers of cups of coffee a day. The driver based measures includes heart rate (values and variability) as well as respiration rate (values and variability) and distraction by mobile phone use in percent.

The camera based metrics utilizes the smartphone camera to gather information about the off-road glance (frequency, duration and percentage), 95th percentile of glance durations, yawning, PERCLOS, blinking (duration, frequency), head movement and saccade frequency. The vehicle measures range from speed (plane measures, variance, speeding percentage), steering measures (angle, entropy), lane deviation, headway (time, distance), car type with regards to sensitivity, acceleration (linear, standard deviation, longitudinal and lateral), yaw rate, brake and accelerometer control as well as control speed and lastly to lateral and longitudinal displacement. The driving performance measures take the lateral distance relative to the midline, time to line crossing, accelerator pedal angle, shift relative to the lateral line, number of line crossings, driving over speed limit, harsh acceleration and deceleration and a smoothness indicator into account.

A variety of different sensors and data is used in the literature for monitoring the driver behavior. It can be viewed in Table III that some sensors are widely used such as Accelerometer, Gyroscope, GPS and others are less investigated such as orientation sensors or the Magnetometer. Similar findings can be found in Table II. For example are neural networks and Support Vector Machines more used then for example dynamic time warping or logistic regression. The Tables II & III reveal that in existing works about driver behavior monitoring smartphone sensors can be used as a means of getting all the relevant data for the classification task which is then processed with different machine learning approaches. Often the chosen machine learning algorithm come with their typical strengths and weaknesses, depending on the data, the scope and the implementation.

IV. Driver Decision Support System

The developed with participation of the authors driver decision support system [18] is aimed at dangerous states detection and recommendation generation [19] based on determined dangerous states as well as context situation in the road (see Fig. 1). The system tracks driver face using the front-facing camera of smartphone mounted in the vehicle windshield as well as information from other sensors to recognize of the vehicle context (speed, acceleration, light level, loudness, and etc.). Based on the images got from front-facing camera the system determines online detected dangerous states [20]. Online detected dangerous states are dangerous states that have to be determined in a small period of time (we identify it as two seconds by default). Two seconds are corresponded to the distance to the vehicle ahead of about thirty meters. The standard speed limit common in urban areas in Russia is sixty km per hour then for this speed thirty meters correspond to two seconds. We identified the following online detected dangerous states: drowsiness and distraction. Based on the determined dangerous states and accumulated context the recommendations for the driver are identified (e.g., for the drowsiness dangerous state it can be: take a nap, drink a cup of coffee, listen of music, cabin airing, singing, dialog with passenger, changing the lights condition).

Along with the detected dangerous states are uploaded to the cloud service together with the accumulated context. Based on this driving statistics the offline detected dangerous states are determined. Offline detected dangerous states are dangerous states that have to be detected in a certain period of time more than two seconds. However, the detection time should be reasonable because if the dangerous state is detected by few hours sometimes the trip can be completed, and such detection is not needed for the driver. In this case, when we talk about offline detected dangerous states on the minutes scale. We have identified the following offline detected dangerous states: aggressive driving, drunk driving, high pulse rate, and stress condition.

To adapt the system to the particular drivers we propose to identify driver behavior patters as well as driver preferences. Identified in the cloud service patterns and preferences are uploaded to the driver smartphone to adapt the dangerous sates detection as well as recommendation generation in the future.

Cloud service provides an access to the representatives of taxi company, logistic company or insurance company in case of the driver that are monitored is an employee of the company or car sharing company in case the driver is the customer [21]. Based on this information the responsible person can make a decision about possibility to continue the trip by the driver.

A prototype of the driver decision support system has been implemented for Android based smartphones (play.google.com/store/apps/details?id=ru.igla.drivesafely) [22]. The prototype at the moment detects two online detected dangerous states (drowsiness and distraction) and uploads text-based measurements to the cloud service related to the cloud services.

TABLE II. MACHINE LEARNING APPROACHES

Citation	Support Vector Machines	k-nearest neighbor	neural network	Bayesian Networks	decision tree	K-means	logistic regression	dynamic time warping	Inference system	discriminant analysis
Júnior Et. al.		X	X		X	X				
Chandrasiri Et. al.	X	X								
Moghaddam and Esmaeel						X				
Zhang Et. al.	X						X			
de Naurois Et. al.			X							
Jabbar Et. al.			X							
Singh Et. al.								X		
Mantouka Et. al.						X				
Mahdi Bejani and Ghatee	X	X	X	X	X				X	
Aksjonov Et. al.			X						X	
Yi Et. al.	X	X			X					X
Streiffer Et. al.			X							
Rahman Et. al.			X	X	X					
Yu Et. al.	X		X							

TABLE III. SENSOR AND INPUT MEASURES

Citation	Smartphone Sensors									Driver based		camera based metrics	vehicle measures	driving performance measures
	Sensors							Calculated						
	Accelero-meter	Gyros-cope	Magneto-meter	gravity sensor	camera	orientation sensor	GPS	Gravity	driving time	information	measures			
Júnior Et. al.		X	X	X									X	
Chandrasiri Et. al.	X	X					X						X	
Moghaddam and Esmaeel										X				
Zhang Et. al.					X							X	X	
de Naurois Et. al.					X		X		X	X	X	X	X	X
Jabbar Et. al.					X							X		
Singh Et. al.	X	X					X	X						
Mantouka Et. al.	X	X	X				X				X		X	X
Mahdi Bejani and Ghatee	X		X				X						X	X
Aksjonov Et. al.														X
Yi Et. al.	X	X					X						X	
Streiffer Et. al.	X	X		X	X	X								
Rahman Et. al.	X	X												
Yu Et. al.	X					X								

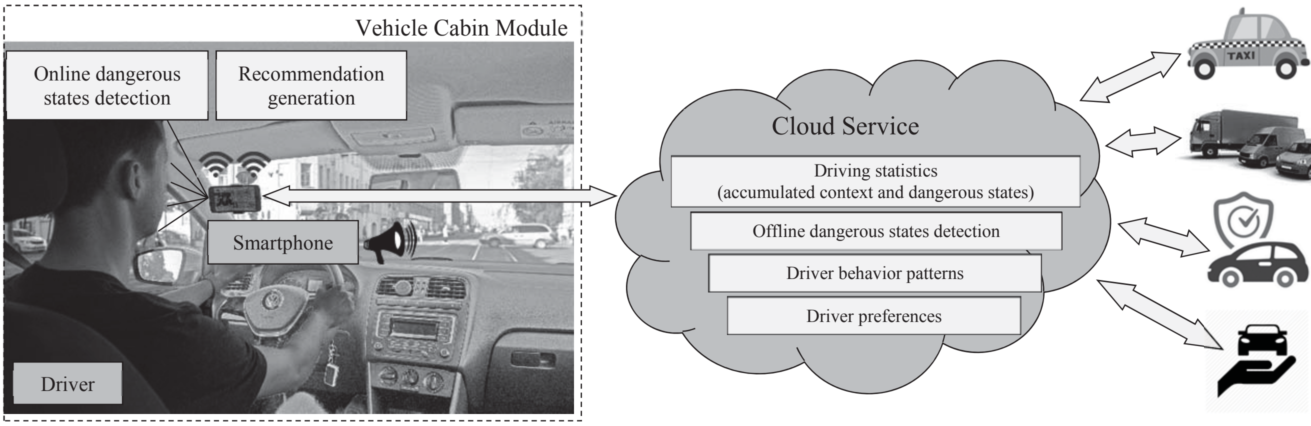

Fig. 1. General scheme of the driver decision support system

V. Proposed Methodology

Based on the information from the literature review regarding common machine learning techniques and corresponding data gathered from smartphones a reference model has been proposed that shows how the modern machine learning approaches can be used for driver decision support system personification (see Fig. 2). When a driver is driving a car and uses the decision support system the smartphone takes place as a means of data collection. The live-data is then uploaded to a cloud in order to perform the identification of abnormal driving behavior. The computation is done by a multi-layer perceptron, a type of neural networks, which proves to be used in similar classification tasks. Ether the behavior of drowsiness or distraction should be identified and based on that an appropriate recommendation should be provided to the affected driver via the smartphone. This would be an ideal “full use case” for the machine learning approach but in reality, tests need to be conducted in order to verify if this kind of an online behavior detection is viable in the real world concerning computation time and resource usage such as battery or internet traffic. The computation time in particular is of special interest in a drive safety system. After all such a system should prevent accidents based on drowsy or distracted driving but if the time to compute the live data and give a proper warning based on the detected behavior exceeds a certain time frame the recommendation might come too late for the driver to react to the situation accordingly. A more feasible way to deploy the machine learning based identification of driver behavior in the current threshold based model of the drive safety system is to use the extended knowledge about the driver behavior from the multi-layer perceptron to update the current thresholds of the drive safety system. Different driving styles and overall driving behavior might be perceived differently for varying drivers. If the individual driver labels their recorded and proposed behavior monitoring correct or incorrect, the system should find better fitting thresholds for the identification of distraction and drowsiness. This way a more personalized experience can be brought to the driver.

Ultimately, the participants themselves are the experts in this kind of a behavior monitoring system and are encouraged to help the classification of behavior by verifying the proposed detected behavior. By confirming the identified behavior the associated data gets labeled accordingly and can be reused in the training of the system to classify the upcoming driving events even more precise. A mentioned problem in literature with this kind of machine learning based system is the challenge of getting a proper classification for a completely new driver with perhaps completely new behavior with which the current model is unfamiliar with and therefore can´t identify the correct behavior with a good accuracy. To address this problem the training of the general model for this system should be considered regularly with a growing database. As an example when new participants use the application and their data is recorded a retraining of the classifier is suitable starting with the step of Data-Preprocessing where the data is normalized and perhaps incomplete data is deleted from the dataset. Afterwards a feature selection is performed in order to find the best set of features that lead to both a satisfying accuracy and a reasonable complexity regarding computation and time efforts. With those preceding steps done the prepared data can be used to perform a training of the model in order to incorporate new behavior of new drivers to the system. This way the proposed model is not only doing its classification task based on a set amount of drivers and their recorded data but also takes completely new driving styles and corresponding new drivers into account. Therefore, a personalized identification of the driver behavior is realizable. Furthermore, there are certain stakeholders that can profit from the knowledge about the different driving behaviors from different drivers. For example can the information be used to give fleet managers of logistics or taxi companies an insight in the different driving behaviors of their drivers in order to incentive appropriate driving styles or conduct training measures to improve the driving behavior if necessary.

VI. Conclusion

This paper aimed at investigating the monitoring of the driver behavior with a smartphone based system and machine learning algorithms. The Tables II & III sum up the found approaches for the proposed task from the literature. Different machine learning approaches as well as many sensors are used in order to detect driver behavior. The developed driver decision support system (see Section IV) can be extended with the proposed methodology of this paper by incorporating a multi-layer perceptron to the current threshold model. This way the classification of the behavior can help personalize the behavior detection and improve the overall accuracy in terms of identifying the abnormal driving behavior by the system. In the real world, the usage of machine learning based classification of driver behavior with smartphone sensors can lead to increased accuracy of driver decision support systems, delivering a more personalized experience and lastly encourage every smartphone user to use this lightweight system compared to expensive and bounded to modern-cars-only driver decision support systems. Therefore, a widespread use and acceptance of this technology seems possible. Not to mention that a machine learning based classification task excel at working with a lot of data which would further improve the quality of the system in a widespread use case. We have identified the following set of features: location, speed, acceleration, PERCLOS, head rotation angles. The features have been chosen based on vehicle position and movement as well as driver behavior. In the future authors are planning to implement neural network learning based on these parameters.

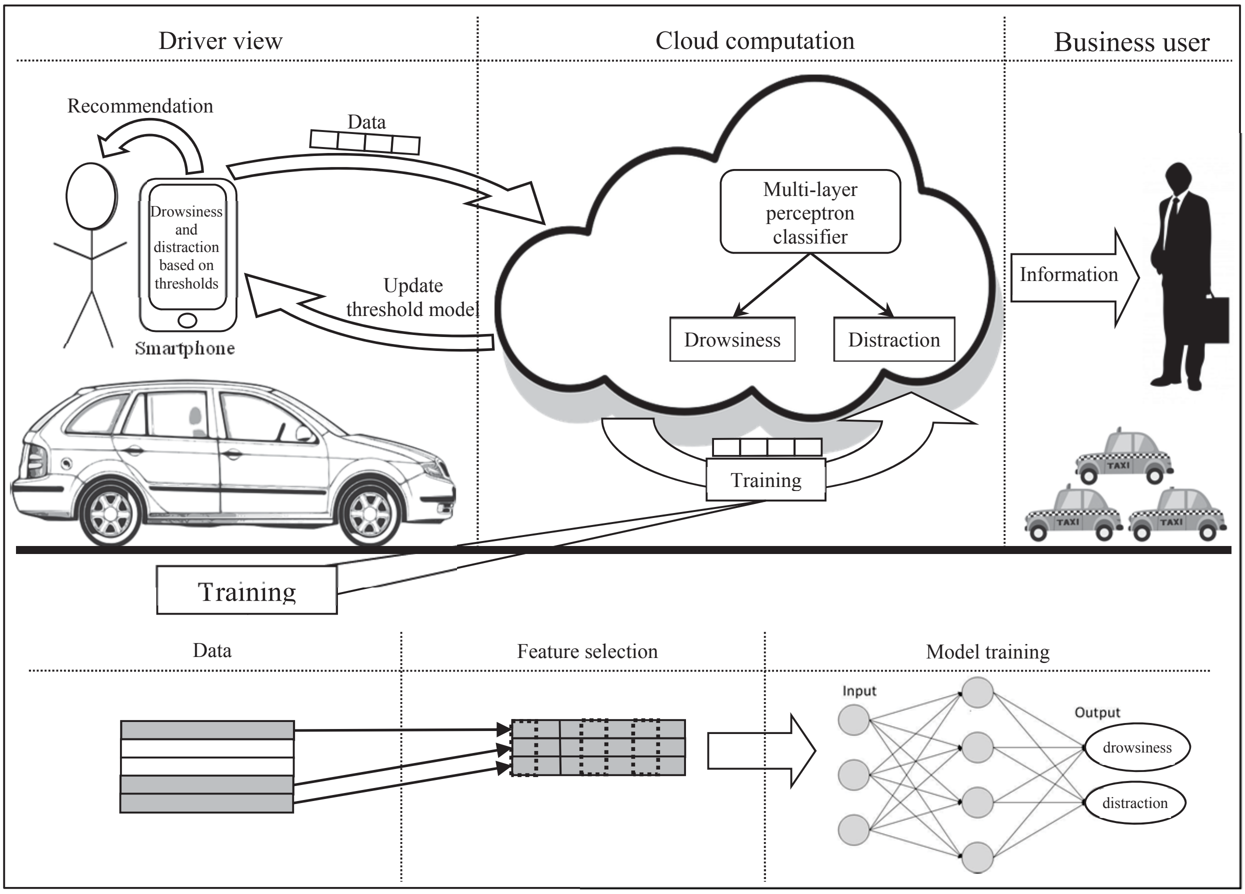

Fig. 2. Reference model for driver decision support based on driving data analysis

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