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Machine Learning Techniques to Identify Unsafe Driving Behavior by Means of In-Vehicle Sensor Data

Emanuele Lattanzi [*], Valerio Freschi

Department of Pure and Applied Sciences, University of Urbino, Piazza della Repubblica 13, 61029 Urbino, Italy

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ABSTRACT

Traffic crashes are one of the biggest causes of accidental death in the way where, every year, more than 1.35 million of people die. In most of them, the main cause is related to the driver's behavior. The driver performs a set of actions on the vehicle commands, such as steering, braking, accelerating or changing gear, which generate a direct response of the vehicle, or other tasks, such as visual, auditory, or haptic related tasks (e.g. looking for items, listening to radio, and using a smartphone), which can still impact on the driving safety. In this work we propose a methodology based on machine learning techniques aimed at recognizing safe and unsafe driving behaviors by means of in-vehicle sensor data. Starting from these signals we compute a set of descriptive features capable to accurately describe the behavior of the driver. Two different classification tools, namely Support Vector Machines and feed-forward neural networks, have been trained and tested on a publicly available dataset containing more than 26 hours of total driving time. The classification results report an average accuracy above 90% for both classifiers and the McNemar test shows no performance difference between the models at the 0.05 significance level, demonstrating a concrete possibility of identifying unsafe driving using in-vehicle sensor data.

1. Introduction

Road safety is becoming a problem afflicting the entire world population every day. The World Health Organization (WHO), in a global status report on road safety launched in 2018, estimated that more than 1.35 million of people die from road accidents each year and that, between 20 and 50 million people suffer non-fatal injuries WHO, 2018.

Although the dynamics of accidents are complex and often their causes are manifold, in most of them, the main cause or one of the contributory causes is the driver's behavior (DB) Obregón-Biosca et al., 2018. DB is a complex concept which describes the result of how the driver controls and manages the car in a given surrounding environment for each particular driving scene Elassad et al., 2020.

Basically, the driver is the main factor influencing the safety of the driving since he/she performs a set of actions on the vehicle commands and controls. For instance, primary tasks such as steering, braking, accelerating or changing gear generate a direct response of the vehicle while secondary tasks, such as visual-related tasks (e.g using vehicle displays or looking for items), auditory-related tasks (e.g. listening to radio or a passenger), and haptic-related tasks (e.g. eating/drinking or using a smartphone), can still impact on the driving safety Nowosielski et al., 2018. Moreover, also the driver state such as the fatigue, stress, or the state of the basic bodily functions directly determines the accident risk Scott-Parker et al., 2013; Wang et al., 2019.

The main purpose of this work is to apply machine learning techniques to identify unsafe driving behaviors by taking advantage of the multitude of sensors already present in modern cars. In fact, all the vehicles produced in recent decades are equipped with several hundreds of sensors and electronic control units (ECUs). Each ECU controls, monitors, and optimizes a particular car function ranging from the fuel injection, to the braking system, and down to the entertainment system. The ECUs are connected together by means of a standard communication bus called *Controller Area Network* (CAN). By connecting to the CAN bus it is possible to read a multitude of parameters and signals, estimated to several tens of gigabyte per hour, which can provide a snapshot of the driving performances Fugiglando et al., Feb 2019.

While the idea of using CAN bus and other motion data to classify driving behaviors by means of machine learning techniques is not novel, a lot of scientific issues remain to be addressed in order to build a reliable and automatic system capable of identify unsafe driving behaviors. First of all, there is not a clear strategy to define when a driving behavior can be objectively labeled as safe or as unsafe (essential requirement for

* Corresponding author.
E-mail addresses: emanuele.lattanzi@uniurb.it (E. Lattanzi), valerio.freschi@uniurb.it (V. Freschi).

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any supervised learning system). Second there is not a common direction on the choice of signals and systems used to gather vehicle motion parameters.

In summary, the main contributions of this work in these directions can be summarized as follows:

- we propose an objective methodology which, starting from the work presented by Eboli et al., 2016, allows labeling each driving interval as safe or as unsafe by looking at the relationship between speed and lateral and longitudinal acceleration of the vehicle;
- we propose to extract several features from in-vehicle sensor data capable to accurately identify safe and unsafe driving behaviors by training two different classification tools, namely a SVM and a feed-forward neural network;

The article is organized according to the following structure: in Section 2 we describe state-of-the-art approaches related to our work, according to the scientific literature; in Section 3 we describe in-vehicle sensors data that can be extracted from the CAN bus; in Section 4 we illustrate the proposed method and the related design choices; in Section 5 we present the results of the experimental evaluation; in Section 6 we report some conclusive remarks and discussions.

2. Related Work

In last decades driving behavior classification has been a widely researched field. Early studies have been made to build dynamic models of the human-vehicle interaction with the aim to create a self-driving system Pentland and Liu, 1999. Others studies have then been conducted to more duly recognize driving manoeuvres such as starting, stopping, passing, etc McNew, 2012.

More recently, several researchers tried to distinguish between normal or aggressive driving behaviors in order to identify unsafe conditions and to reduce possible traffic crashes. In this domain, different machine learning tools have been successfully applied both through supervised and unsupervised learning techniques. One of the major limitations of supervised learning models to the classification of driving styles is due to the difficulty of having the external knowledge (ground truth) of what is safe and what is unsafe. On the other hand, unsupervised models hardly manage to produce classifications which can easily be related to driving safety.

In the studies based on supervised learning techniques, several approaches have been proposed to label a driving behavior. These are ranging from asking people to deliberately drive dangerously in public roads, to imposing drivers to repeat, in a controlled environment, synthetic tasks, such as braking, accelerating, turning, etc, both in aggressive and in non-aggressive ways Carmona et al., 2016; Ferreira et al., Apr 2017; Shahverdy et al., Jul 2020. Although these experiments are scientifically interesting, they suffer from the non-objectivity of the experimental conditions.

A second widespread approach, instead of classifying driver behaviors based on security of the maneuvers, tries to identify a driver relying on the fact that everyone drives differently and that these differences can represent a unique "signature" of the driver Hallac et al., 2016; Martinelli et al., 2018; Zhang et al., Mar 2019. These studies are based on the fact that if the classifiers are able to successfully recognize people's different driving styles, then they can also distinguish between safe and unsafe conditions but, in fact, there is no measured evidence of this ability.

In our work, we propose the adoption of an objective methodology to reconstruct the ground truth by labeling each driving time window as safe or unsafe. The labels are calculated exploiting the relationship between speed and longitudinal and lateral accelerations of the vehicle, according to the work presented by Eboli et al., 2016. Then, two different classification tools, namely a SVM and a feed-forward neural network, have been trained and tested over on publicly available dataset containing more than 26 hours of total driving time spent by ten different drivers.

From the point of view of the signals and systems used to collect data from the vehicle, it is possible to distinguish between approaches that make use of in-vehicle sensor data, which substantially intercept CAN bus parameters, and approaches which extract vehicle motion data such as acceleration, GPS tracks, gyroscope signals, etc. from ad-hoc installed sensors or from a smartphone anchored on the car.

For instance, Carmona et al., 2016, make use of a hardware tool, created ad-hoc, which integrate GPS and Inertial Measurement Unit (IMU) with data read from the CAN bus. Several experiments have then been conducted where ten drivers have been asked to drive the same route twice, in a normal and aggressive way respectively.

Several other studies have been conducted where CAN bus signals have been combined with those from different external sensors such as web cams and microphones to monitor the driver's reactions Choi et al., 2007; Li et al., 2013.

More recently, several researchers proposed to use signals extracted by mobile smartphone sensors such as accelerometer, gyroscope, magnetometer, GPS, cam, and microphone). For instance, Ferreira et al., Apr 2017 exploited accelerometer, magnetometer, and gyroscope of a smartphone to identify driving events such as aggressive braking, aggressive acceleration or aggressive turns.

Van Ly et al., 2013 have coupled smartphone sensor data with CAN bus data for identifying acceleration, braking and turning events, reaching 60% of accuracy.

Shahverdy et al., Jul 2020 have classified driving styles in: i) normal; ii) aggressive; iii) distracted; iv) drowsy; v) drunk. In particular, the authors asked several drivers to emulate each driving class while a smartphone, coupled with the CAN bus data, was recording several signals.

In our work we propose to extract several features only from in-vehicle sensor data by reading signals available on the CAN bus. We do not consider it appropriate, for instance, adding any signals such as positioning from the GPS or such as video and audio from the smartphone sensors which, if incorrectly used, could compromise the driver's privacy and then reduce the use and the diffusion of the technological solution.

3. In-Vehicle Sensors

Modern automobiles contain up to 50 electronic control units (ECUs) which are connected together. These ECUs manage and monitor each main car functionality such as traction control, air conditioning, fuel injection, braking system, etc. In order to standardize the communication between ECUs, Robert Bosch introduced in the early 1990 a bus called Controller Area Network (CAN) Bosch, 1991. Thanks to the CAN bus, each ECU can communicate with others by sending broadcast packets so that the receiver ECU can autonomously decide whether to read or not the packet. The CAN bus protocol defines generic communication standard which concerns only the physical and data layers of the ISO/OSI stack so, for these reason, a high level protocol specifically created for vehicles and called On Board Diagnostics (OBD) has been introduced Birnbaum and Truglia, 2001. The OBD protocol operate over the CAN bus protocol in the way that a ECU generate a OBD message which is then encapsulated on a CAN message and finally broadcast to the bus. The receiving ECU extract the OBD message from the CAM message and then processes it. The OBD protocol has become mandatory in USA for vehicles manufactured since 1996 (also referred as OBD-II) while the European version, called European On Board Diagnostics (EOBD) has been introduced in the European Union since 2001.

The OBD protocol also defines a physical connector that must be present in each vehicle for connecting compatible instruments which can interact with ECUs by reading and writing OBD messages on the bus. Although it is technically possible to access any information generated by the numerous ECUs installed on the car, OBD standardizes a subset of all sensors signals that can be monitored by external instruments in addition to a standardized series of diagnostic trouble codes (DTCs). The monitoring sensors are addressed by ”parameter identification numbers” or PIDs which are defined in a standard called SAE J1979.

The mandatory sensors specified in the ODB-II standard are primarily intended for emissions inspections including, for instance, sensors for vehicle speed, engine revolution speed, engine load, throttle position, fuel and air pressure, fuel and air temperature, and so on. Cars manufacturers also define additional PIDs specific to their vehicles granting access to other vehicle signals such as brake pressure, steering angle, wheel speeds, etc. but, because these are not part of any standard, it will not always be possible to access at this notable information.

4. Proposed Method

The main goal of this study is to construct a supervised learning binary classifier to automatically identify safe and unsafe behaviors during driving. In this section we will take an in-depth look at the proposed methodology by highlighting each processing phase.

4.1. Data Gathering

In this study we made use of the publicly available dataset (https://ocslab.hksecurity.net/Datasets/driving-dataset) presented by Kwak et al., 2016. The dataset is made up 94,380 items each of which contains 51 different signals collected from in-vehicle sensors by means of the OBD-II bus. Each sensor was sampled every second for about 26 hours of total driving time during which ten drivers covered more than 460 km in South Korea. The entire dataset has been created using a recent model of KIA Motors Corporation. The driving path consists of three types of city way, motor way, and parking space.

The 51 signals can be grouped into four categories according to the sector of the car they are going to measure. In particular, the first 12 signals monitor engine intake and injection system reporting, for instance, the value of throttle position, fuel pressure, intake air pressures, and so on. Signals from 13 to 32 describe dynamic engine parameters such as engine speed, engine torque, load value, etc. From 33 to 43 the signals report transmission parameters such as current gear, clutch actuation, brake pressure, and wheels speed while the last 8 signals are related to the dynamic of the vehicle. In particular, they measure speed, longitudinal and lateral acceleration, steering wheel speed and angle, and so on. Notice that, this dataset contains more signals than those specified by the OBD-II standard and some of these are usually not recordable by common OBD-II interfaces.

4.2. Features Extraction

Starting from the 51 signals in the dataset, only those most significant for the estimation of driving behavior were chosen. In particular we focused on:

- Vehicle speed
- Engine speed
- Engine load
- Throttle position
- Steering wheel angle
- Brake pedal pressure

Vehicle speed, engine speed and load represent quantities that are indirectly related to the driver action but can be perceived during driving and can reflect an attitude of the driver. Throttle position, steering wheel angle, and brake pedal pressure, on the contrary, directly describe the driver actions.

Notice that, only the first four signals (i.e. Vehicle speed, Engine speed, Engine load, and Throttle position) are compliant with the OBD-II standard so that they can be extracted from all vehicles produced after the year 2001. The availability of steering wheel angle and brake pedal pressure signals depends on the vehicle manufactures policy so that it is not guaranteed that this information can be accessed on all cars.

The recorded tracks have been divided in time windows in each of which, for each signals, three set of descriptors have been computed. In particular, the first set (*Base*) contains basic statistical descriptors aimed at capturing data tendency and variability. These descriptors are: *i)* average; *ii)* maximum value; *iii)* standard deviation; *iv)* median value. The second set contains Hjorth parameters (*Hjorth*), namely: i) Activity; ii) Mobility; iii) Complexity. The third set is built with Kurtosis and Skewness parameters aimed at capturing the shape (*Shape*) of the data. For what concerns the *Base* set, while average and median value can identify continuous misuse of a command or a tendency to drive, for instance, over the posted speed limits, the maximum value describes an instantaneous misbehavior. In addition, standard deviation can reveal a high rate of change which, in many occasions, implies aggressive behavior. For instance, an high standard deviation on the engine speed or on the throttle position reveals fast and erratic engine control that suggests aggressive driving. In the same way, an high standard deviation on the steering wheel angle can capture fast changes of lanes and strong lateral movements.

On the other hand, Hjorth parameters are commonly used in feature extraction to capture the main characteristics of a signal in the frequency domain. In fact, Hjorth activity represents the power of the signal, the mobility its mean frequency, and the complexity measures its change in frequency Hjorth, 1970.

Kurtosis and Skewness are used to describe, respectively the degree of dispersion and symmetry of the data. In particular, Kurtosis is a measure of whether the data are heavy-tailed or light-tailed relative to a normal distribution while, Skewness measures how much data differ from a completely symmetrical distribution Kim and White, 2004.

Starting from the work presented by Carmona et al., 2016, in which the authors process OBD-II signals using 20 seconds time windows to distinguish between normal or aggressive driving behaviors, we consider a shortest window lasting 10 seconds with 50% overlap. Notice that, other approaches such as those aimed at recognising drunk or fatigued drivers, traditionally, make use of shorter time windows, for instances, in the order of 5 or 2 seconds. Normally, in fact, these works are based on signals gathered from digital camera or from inertial accelerometers and are aimed at identifying particular driver’s states which can interfere with the ability to maneuver a vehicle Dai et al., 2010; Friedrichs and Yang, 2010; You et al., 2012; Clausse et al., 2019; Eftekhari and Ghatee, 2019; Osman et al., 2019. To better highlight the impact of the window length on the overall performance, we present in this work a deep sensitivity analysis of the classifiers with respect to this parameter.

After feature extraction, we obtain 18,874 time windows each of which has been characterized with 54 descriptors.

4.3. Data Labeling

One of the aims of this work is to propose an objective method to label the result of the driver behavior, at any given moment, as safe or as unsafe by analysing the dynamic of the vehicle. Each supervised learning algorithm needs training data accompanied by true classification labels to lead the learning process. In driving behavior classification, having labels that identify the behavior as safe or unsafe is far from trivial both for the safety concept of driving itself, and for the difficulty of obtaining objective information.

For this purpose we refer to the work presented by Eboli et al., 2016. In this work the authors combine vehicle speed, longitudinal, and lateral accelerations to classify car drivers’ behavior as safe or unsafe analysing the dynamic equilibrium of the vehicle. In particular, the vehicle is subject to an $\overline{a}$ acceleration vector in the horizontal plane which is the vector sum of a longitudinal (a_{lon}) acceleration, in the same direction of the motion, and a lateral acceleration (a_{lat}), perpendicular to the

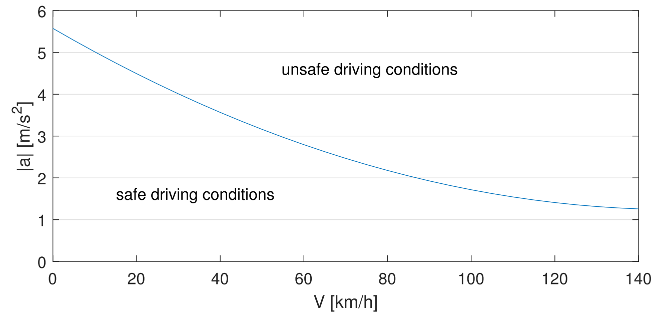


Fig. 1. The $(V, |\overline{a}|)$ plane split up into safe and unsafe driving conditions according to Eq. 8.

direction of the motion. According to the second law of Newton, the vehicle is subject to a force, in the horizontal plane, which can be calculated with Eq. 1 where m is the mass of the vehicle.

$$F = m \cdot \overline{a} \tag{1}$$

In normal conditions the force F is balanced by a centripetal force (F_c) which depends on the side friction (μ) between tyres and road pavement, and by the mass (m) of the vehicle as in the Eq. 2.

$$F_c = m \cdot g \cdot u \tag{2}$$

When the vehicle reaches its limit equilibrium, F is equal to F_c. In this condition, the tyres are unable to sustain higher forces and any increasing in lateral or longitudinal acceleration entails a loss of grip with possible car skidding.

The relation between the maximum value of the lateral friction (μ_{latMax}) and speed (V), expressed in kilometres per hour, under dry pavement conditions is reported by Lamm et al., 1999 and it is described by Eq. 3

$$\mu_{latMax} = 0.214 \cdot (\frac{V}{100})^2 - 0.640 \cdot (\frac{V}{100}) + 0.615 \tag{3}$$

Lamm et al. also define the relationship between lateral (μ_{lat}) and longitudinal friction (μ_{lon}) with the Eq. 4.

$$\mu_{lat} = 0.925 \cdot \mu_{lon} \tag{4}$$

By combining Eq. 3 and Eq. 4 the maximum friction value in the longitudinal direction (μ_{lonMax}) can be calculated following Eq. 5

$$\mu_{lonMax} = 0.198 \cdot (\frac{V}{100})^2 - 0.592 \cdot (\frac{V}{100}) + 0.569 \tag{5}$$

Since in the limit conditions we need to consider the max value of the friction instead of the its function, a conservative assumption is to consider the maximum friction value in both axes equals to the minimum between μ_{latMax} and μ_{lonMax}. In this way we obtain the maximum friction value (μ_{Max}) for both axes as described in Eq. 6

$$\mu_{Max} = 0.198 \cdot (\frac{V}{100})^2 - 0.592 \cdot (\frac{V}{100}) + 0.569 \tag{6}$$

Replacing the μ value in Eq. 2 with Eq. 6 the maximum centripetal force (F_{cMax}) can be calculated as follows (Eq. 7).

$$F_{cMax} = m \cdot g \cdot \left[0.198 \cdot \left(\frac{V}{100}\right)^2 - 0.592 \cdot \left(\frac{V}{100}\right) + 0.569 \right] \tag{7}$$

Combining Eq. 7 with Eq. 1 we obtain a relationship between the maximum acceleration vector in the horizontal plane, tolerated by the vehicle, and the vehicle speed, as reported by Eq. 8.

$$|\overline{a}_{Max}| = g \cdot \left[0.198 \cdot \left(\frac{V}{100}\right)^2 - 0.592 \cdot \left(\frac{V}{100}\right) + 0.569 \right] \tag{8}$$

Eq. 8 defines a quadratic relationship between acceleration and speed which shows as the tolerated acceleration decreases when speed increases. Plotting this function on a $(V, |\overline{a}|)$ plane splits out it in two areas representing safe and unsafe driving domains. In particular, the points falling outside the curve represent unsafe driving conditions while those inside are safe (See Fig. 1).

Using speed, lateral, and longitudinal accelerations, contained in the dataset described in Section 4.1, each time window of each track has been marked with a binary label generated by means of Eq. 8. In particular, about the 69% of the data (corresponding to 13,023 records), have been labeled as ”safe” and the remaining about 31% as ”unsafe” (5,850 records). Then, labeled data have been used to train the classifiers and to evaluate the resulting performances. Notice that, lateral and longitudinal accelerations have not been included into the classification features to avoid the possibility that the classifier could learn the relationship between speed and acceleration that led to the definition of the classification labels and then distort the results.

It is worth noticing that, while Eboli *et al.* originally proposed to adopt specific kinematic parameters as a proxy to gain information regarding safe/unsafe driving patterns, in this work we make use of these results to label datasets for training and testing machine learning models. In this way, we achieve a reliable way of measuring the performance of our (and other) approaches, thus overcoming the inherent difficulties posed by the availability of ground truth data.

4.4. The Classifiers

To proposed method is based on two different learning classification tools: *i)* support vector machine and *ii)* artificial neural network. Both of them have been trained and tested on the complete dataset described in Section 4.1.

4.4.1. Support Vector Machines (SVM)

SVM are supervised learning models associated with learning algorithms for regression and classification. They are mainly used to solve classification problems with a reduced number of samples. Given a set of training data, each of which is labeled with the membership class, a training algorithm builds a model that assigns the new data (testing data) to one of the classes. A SVM model is a representation of the input data as points in space, mapped in such a way that the data belonging to the different classes are separated by a space as large as possible. The new data are then mapped in the same space and the prediction of the category to which they belong is made on the basis of the side on which it falls.

The main goal of the SVM is to find a hyperplane that best divides the dataset into the desired classes. In addition to the simple linear classification, it is possible to make use of the SVM to effectively carry out nonlinear classifications using non linear kernel methods which implicitly maps input data in a multi-dimensional feature space.

For the purpose of this work, a binary-class SVM with a cubic polynomial kernel has been trained Steinwart and Christmann, 2008. We also considered other kernels (i.e. linear, quadratic or Gaussian functions), however, these did not reach the performances of the cubic kernel.

4.4.2. Artificial Neural Network

A neural network is a computational model composed of artificial *neurons*, inspired by a simplification of a biological neural network. They can be used to simulate complex relationships between inputs and outputs that other analytical functions cannot represent. An artificial neural network receives external signals on a layer of input neurons, each of which is connected with numerous hidden internal neurons,

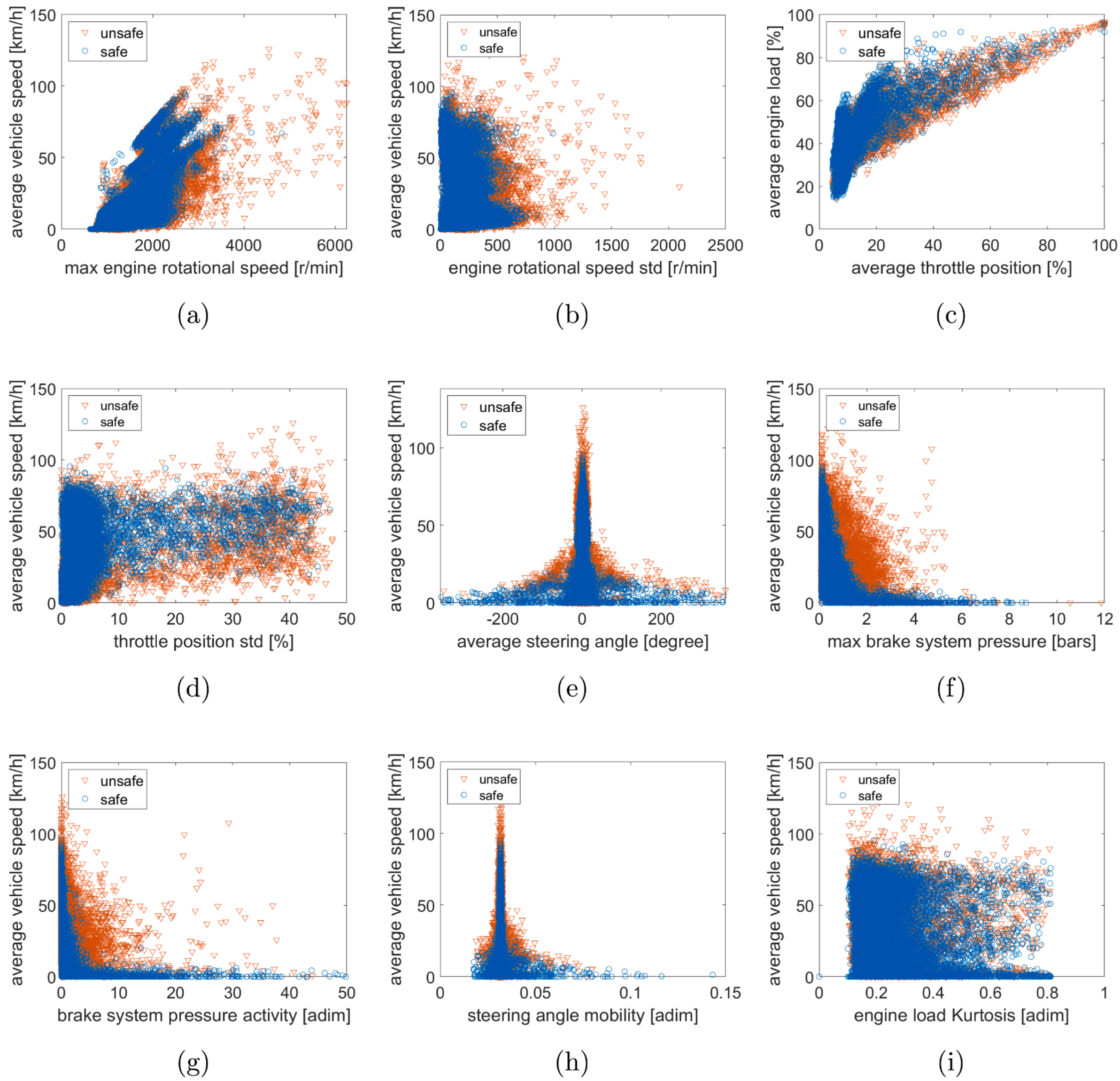


Fig. 2. Scatter plots of several features calculated starting from the dataset tracks.

organized in several levels. Each neuron processes the received signals and transmits the result to subsequent neuron. The aforementioned neurons receive stimuli at the input and process them. The processing entails the evaluation of a transfer function on the weighted sum of the received inputs. The weight indicates the synaptic effectiveness of the input line and serves to quantify its importance. The learning capabilities of the neural network are achieved by adjusting the weights in accordance with the chosen learning algorithm. Different training algorithms have been proposed in literature together with different performance metrics Hassoun et al., 1995.

In this work we used a simple feedforward network with a single hidden layer composed of 50 neurons. The network was trained by means of a backpropagation Levenberg–Marquardt algorithm Foresee and Hagan, 1997 with a traditional mean square error (MSE) performance function.

5. Experimental Results

In this section we report the results obtained with the proposed method. First of all we analyse the qualitative adequacy of the proposed features in classifying safe and unsafe records. Then we describe the performance achieved by SVM and neural network classification tools.

5.1. Feature Analysis

The tracks of the dataset presented in Section 4.1 have been processed using Matlab®. For each of the 18,874 time windows, the 54 proposed features have been extracted for a total amount of 1,019,196 values.

Fig. 2 shows different scatter plots of some representative features. Each point has been labeled with a blue or a red triangle respectively if it belongs from a ”safe” or from a ”unsafe” window.

In particular, Fig. 2.(a) and (b) plot, respectively, the maximum value and the standard deviation of the rotational speed of the engine versus the average vehicle speed. Interestingly, unsafe behaviors are associated more frequently at high engine r.p.m. when the vehicle speed is low. On the contrary, high and rapid variations on the engine speed (high standard deviation) are always associated to unsafe driving and when driving at high speed (more than 80 km/h) also a reduced engine speed variation (lower of 500 r.p.m.) is frequently associated to an unsafe behavior.

Fig. 2.(c) reports the average steering angle versus the average vehicle speed. As can be expected, high steering angle at low vehicle speed are normal behaviors while, the higher the speed, the lower the safe steering angle.

Table 1
Confusion matrices and classification performance of SVM (a) and Neural Network (b) while trying to distinguish safe and unsafe driver behaviors using only the features extracted from the OBD-II compliant signals. The reported values represent the average and the standard deviation calculated over the 5x2 cross validation test.

hline SVM			
true class	predicted class		Avg
	Safe	Unsafe	
Safe	**0.9351**	0.0649	-
Unsafe	0.4077	**0.5923**	-
Precision	0.8301±0.0067	0.8131±0.0385	0.8215±0.0200
Recall	0.9351±0.0190	0.5923±0.0205	0.7637±0.0113
F_1 score	0.8794±0.0096	0.6847±0.0176	0.7915±0.0144
Accuracy	0.8256±0.0123	0.8256±0.0123	0.8256±0.0123
[Neural Network] true class	predicted class		Avg
	Safe	Unsafe	
Safe	**0.9330**	0.0670	-
Unsafe	0.3676	**0.6324**	-
Precision	0.8523±0.0026	0.8060±0.0087	0.8291±0.0040
Recall	0.9330±0.0043	0.6324±0.0086	0.7827±0.0032
F_1 score	0.8908±0.0016	0.7086±0.0045	0.8052±0.0027
Accuracy	0.8411±0.0022	0.8411±0.0022	0.8411±0.0022

Table 2
Confusion matrices and classification performance of SVM (a) and Neural Network (b) while trying to distinguish safe and unsafe driver behaviors using OBD-II and brake pressure features. The reported values represent the average and the standard deviation calculated over the 5x2 cross validation test.

[SVM]			
true class	predicted class		Avg
	Safe	Unsafe	
Safe	**0.9458**	0.0542	-
Unsafe	0.2968	**0.7032**	-
Precision	0.8716±0.0032	0.8590±0.0069	0.8653±0.0033
Recall	0.9458±0.0035	0.7032±0.0090	0.8245±0.0038
F_1 score	0.9072±0.0017	0.7733±0.0049	0.8444±0.0030
Accuracy	0.8683±0.0024	0.8683±0.0024	0.8683±0.0024
[Neural Network] true class	predicted class		Avg
	Safe	Unsafe	
Safe	**0.9513**	0.0487	-
Unsafe	0.2750	**0.7250**	-
Precision	0.8872±0.0070	0.8675±0.0076	0.8774±0.0059
Recall	0.9513±0.0032	0.7250±0.0199	0.8381±0.0098
F_1 score	0.9181±0.0039	0.7897±0.0132	0.8573±0.0077
Accuracy	0.8821±0.0061	0.8821±0.0061	0.8821±0.0061

Conversely, Fig. 2.(d) shows that a rapid variation of the throttle position is more prone to bring to unsafe conditions when the vehicle speed is low. This is due to the fact that, when the vehicle is traveling at low speeds, probably, a low gear is engaged and, in this condition, a rapid increase in the throttle pressure entails a rapid increase of the engine speed. This produces an high driving torque and an high vehicle acceleration. On the other hand, when a higher gear is engaged (higher speed) the acceleration produced by a rapid variation on the throttle position is reduced and the effects on the vehicle are more easily controllable.

Fig. 2.(e) plots the average throttle position versus the average engine load. The highest concentration of unsafe points in the north-east quadrant of the figure suggests that a high value of the throttle position (i.e. high pressure on the throttle) when the engine load is high can generates unsafe conditions.

The pressure recorded on the brake system, plotted versus the average speed of the vehicle (Fig. 2.(f)), shows a clear separation between safe and unsafe points. The former are the points closer to the two axes where, either the pressure is high and the speed is low, or the pressure is low and the speed is high. The latter, instead, fall on high pressure and high speed positions. This is quite intuitive given that an energetic action on the brake pedal while traveling at high speed is due to an emergency situation or to an aggressive driving. In both cases it can be considered a unsafe driving.

Fig. 2.(g) plots the Hjorth activity versus the average speed of the vehicle. Also in this case, safe and unsafe samples can be clearly distinguished. On the contrary, the Hjort mobility of the steering angle (Fig. 2.(h)) and the Kurtosis of the engine load (Fig. 2.(i)), plotted versus the average vehicle speed, do not allow easy parting of safe and unsafe data.

5.2. Classification Results

For the evaluation of the performance of the two classifiers we used the 5x2 cross validation test. This test involves running 5 replications of a 2-fold cross-validation test where, in each replication, the whole available data is randomly partitioned into two equal-sized sets used, respectively, for training and for testing the classifier. This test is particularly suitable in situations where the learning algorithms are not too complex and they can be easily executed at least ten times Dietterich, 1998. At the end of the ten runs, the average and the standard deviation of the performance metrics have been calculated.

The following metrics have been used to evaluate performance:

$$Precision = \frac{TP}{TP + FP} \quad (9)$$

$$Recall = \frac{TP}{TP + FN} \quad (10)$$

$$F_1 score = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \quad (11)$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (12)$$

where *TP* are the true positives, *TN* the true negatives, *FP* the false positives, and *FN* the false negatives.

Notice that, in this section, we report the results obtained while adopting the configuration parameters and features producing higher performances as it results from the analysis reported in Section 5.3 .

Table 1 reports the classification performances obtained by the SVM and the neural network classifiers when using only the OBD-II compliant signals (i.e. vehicle speed, engine speed, engine load, and throttle position). The reported values represent the average and the standard deviation calculated over the 5x2 cross validation test. In particular, sub-Table 1.(a) reports the performances obtained by the SVM classifier. The total classification accuracy reaches about 83% with average precision and recall respectively of about 82% and 76%. Although the average classification performances are noteworthy, they result appreciably unbalanced in the two classes. In fact, the precision and the recall calculated for the ”safe” class exceed 83% and 94% respectively while, for the ”unsafe” class they are 81% and 60%. Also the F_1 score metric highlights a great imbalance in performances with the value of about

Table 3
Confusion matrices and classification performance of SVM (a) and neural network (b) while trying to distinguish safe and unsafe driver behaviors using OBD-II, brake pressure, and steering angle features. The reported values represent the average and the standard deviation calculated over the 5x2 cross validation test.

[SVM]			
true class	predicted class		Avg
	Safe	Unsafe	
Safe	**0.9453**	0.0547	-
Unsafe	0.1898	**0.8102**	-
Precision	0.9139±0.0035	0.8747±0.0074	0.8941±0.0047
Recall	0.9453±0.0035	0.8102±0.0083	0.8778±0.0049
F_1 score	0.9294±0.0028	0.8413±0.0065	0.8859±0.0046
Accuracy	0.9021±0.0039	0.9021±0.0039	0.9021±0.0039
[Neural Network]			
true class	predicted class		Avg
	Safe	Unsafe	
Safe	**0.9591**	0.0409	-
Unsafe	0.1757	**0.8243**	-
Precision	0.9307±0.0044	0.8858±0.0112	0.9083±0.0059
Recall	0.9591±0.0055	0.8243±0.0116	0.8917±0.0057
F_1 score	0.9447±0.0031	0.8538±0.0076	0.8992±0.0053
Accuracy	0.9179±0.0044	0.9179±0.0044	0.9179±0.0044

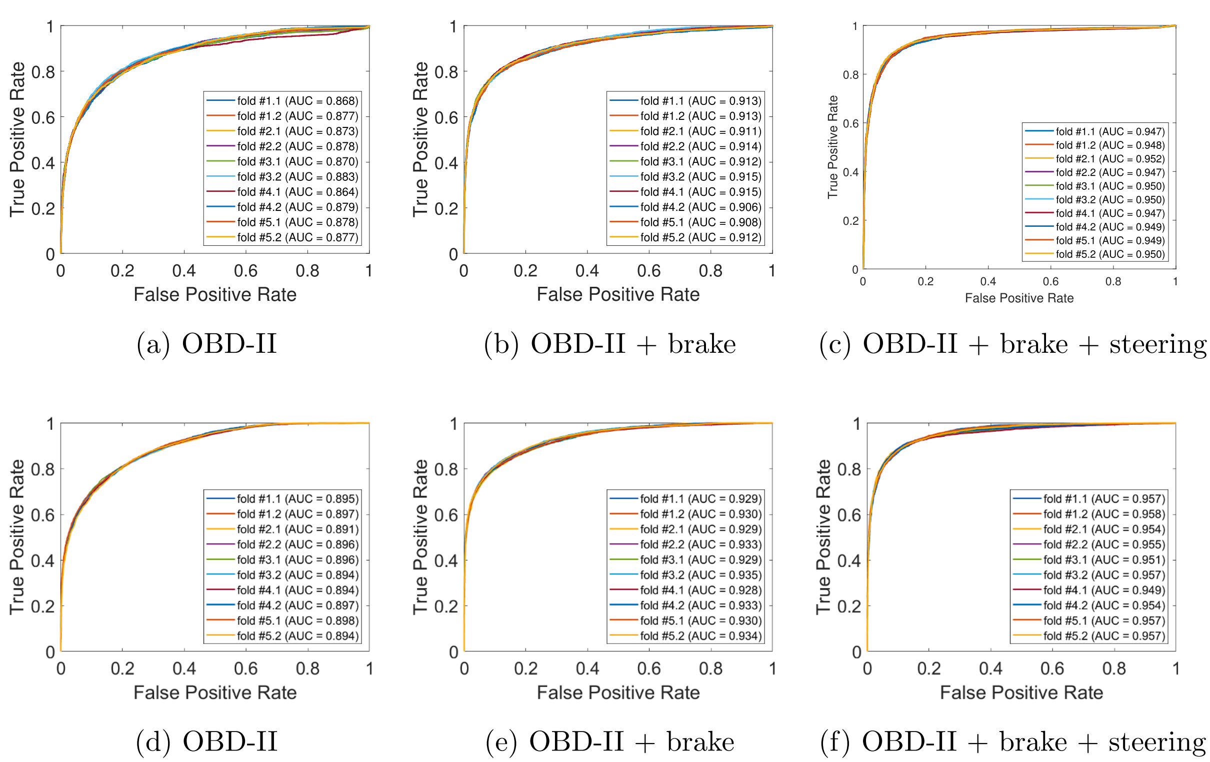
88% for the "safe" class and with about 68% for the "unsafe". In summary, although the remarkable average accuracy, the appreciably high number of false negatives, found in the "unsafe" class (about 40%), reduces the effectiveness of the classification method. Interestingly, the reduced entity of the standard deviations shows a good reproducibility of the results.

Results obtained with the neural network tool (Table 1.(b)) confirm the same trend apart from a remarkable improvement (of about four percentage point) for the recall of the "unsafe" class.

Table 2 reports the results obtained in the same experiments with the only difference that the features used include, in addition to the OBD-II compliant signals, the features calculated from the pressure of the braking system. Both SVM (a) and neural network (b) show an appreciable classification improvement in terms of average metrics with a more pronounced increase for the neural network. In particular, in this case, precision and recall for the "safe" class reach, respectively, 89% and 94% while the "unsafe" class shows an increase of about 6 percentage points both in precision and of about 9 percentage points in recall, reaching 86% and 73% respectively. Undoubtedly, the information content brought by the added features has allowed the classifiers to more easily disentangle some ambiguous driving behaviors and to classify them correctly. For instance, a decrease in the vehicle speed can take on different meanings if due to a strong action on the braking system or if it is simply the consequence of a change on the road gradient. So that, an increase in the braking system pressure, when the vehicle is traveling at high speed, can be easily recognized as an unsafe behavior.

In the last experiment the classifiers have been tested by further adding the features extracted from the steering angle signal. Table 3 reports the related results. With both tools, the classification performances reach really high values with an average accuracy up to of about 92%. Also for the "unsafe" class the precision and recall values are always higher than 87% and 81% respectively. Moreover, for the "safe" class, the neural network classifier, which achieves the best performances, obtains precision and recall values in the order of about 93% and 96%.

As a further measure of performance, for both classifiers, the ROC curves have been calculated in each features configuration. Fig. 3 shows the ROC curves, together with the calculated area under curve (AUC), obtained for the "unsafe" class, in each of the runs of the 5x2 cross validation test. In particular, the first row of subfigures (a, b, and c) are



(a) OBD-II (b) OBD-II + brake (c) OBD-II + brake + steering

(d) OBD-II (e) OBD-II + brake (f) OBD-II + brake + steering

Fig. 3. ROC curves of SVM (a,b, and c) and Neural Network (d, e, and f) for different in-vehicle sensor signals.

Table 4
Results of three variations of the McNemar test.

	OBD-II			OBD-II+br			OBD-II+br+st		
	asym	mid-*p*	exact	asym	mid-*p*	exact	asym	mid-*p*	exact
h	true	true	true	false	false	false	false	false	false
p	0.0042	0.0042	0.0046	0.1618	0.1620	0.1737	0.8230	0.8231	0.8479
eSVM	0.1744	0.1744	0.1744	0.1317	0.1317	0.1317	0.0979	0.0979	0.0979
eNN	0.1589	0.1589	0.1589	0.1179	0.1179	0.1179	0.0821	0.0821	0.0821

Table 5
SVM forward feature selection results

Features	Accuracy	Precision	Recall	F1score
B	0.9021 ± 0.0039	0.8941 ± 0.0047	0.8778 ± 0.0049	0.8859 ± 0.0046
H	0.8335 ± 0.0020	0.7870 ± 0.0029	0.8158 ± 0.0030	0.8011 ± 0.0024
S	0.7197 ± 0.0025	0.6364 ± 0.0044	0.6730 ± 0.0038	0.6542 ± 0.0034
B+H	0.8977 ± 0.0033	0.8693 ± 0.0055	0.8890 ± 0.0029	0.8790 ± 0.0040
B+S	0.8864 ± 0.0028	0.8604 ± 0.0032	0.8748 ± 0.0041	0.8675 ± 0.0032
B+H+S	0.8804 ± 0.0028	0.8507 ± 0.0045	0.8695 ± 0.0032	0.8600 ± 0.0035

related to the SVM classifier while the second row (d, e, and f) to the neural network. Also in this case, the classification performances of both classifiers show a well defined increasing trend if brake and steering signals are added to the selected features. Moreover, the strong overlap of the different ROC curves, obtained in each 5x2 runs, demonstrates a high degree of reproducibility.

Finally, in order to statistically assess whether the accuracies of the two classification models are different, three variations of the McNemar test have been performed that is: i) asymptotic test; ii) exact-conditional test; iii) mid-*p*-value test Fagerland et al., 2013.

Table 4 reports the results of the three significance tests conducted while using only OBD-II, or OBD-II plus brake pressure, or OBD-II plus brake pressure and steering angle, as signals used to compute the classification features. For each test, the logical value h is reported which represents the test decision when testing the null hypothesis that the SVM and the neural network classifiers have equal accuracy for predicting the true class. So, a false value indicates that the null hypothesis is not rejected with a confidence level of 95%. Moreover, also the p value and the SVM and neural network classification errors are reported (eSVM and eNN).

The three variants of the McNemar test agree not to reject the null hypothesis when using the OBD-II signals with brake pressure or OBD-II signals with brake pressure and steering angle. On the other hand, when using only OBD-II signals, the null hypothesis needs to be rejected so that the accuracies of the two classification models can not be considered equivalent.

These experimental results demonstrate the concrete possibility of identifying unsafe driving styles by simply analyzing the in-vehicle sensor data thanks to the great effectiveness and reliability of the proposed method.

5.3. Sensitivity to the configuration parameters

In order to evaluate the sensitivity of the models to the selected features, we used the forward feature selection method Liu and Yu, 2005. Forward feature selection relies on an objective function (e.g. the accuracy) which is used as a criterion to evaluate the impact of adding a features from a candidate subset. We applied this strategy to highlight how different groups of features contribute to the overall performance of the classifiers. In particular, features have been grouped into three main groups namely: base (B), Hjorth (H), and shape (S). First of all, each classifier has been tested with only the B group and then the other groups have been added step by step. Notice that each group was treated as an atomic unit which can be added or removed as a whole.

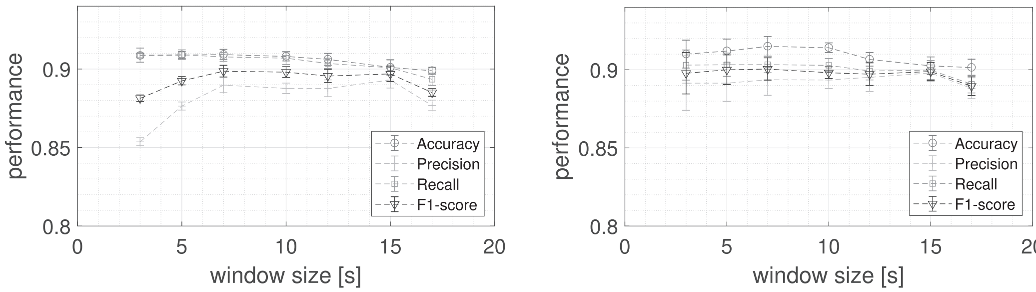
Table 5 and Table 6 show, respectively, the results of the features forward selection experiment for the SVM and the neural network classifiers. In particular, the average values of the accuracy, precision, recall, and F1-score, resulting from a set of 5x2 cross validation tests, have been reported. Each 5x2 test has been conducted using different combinations of the groups of features(*Base, Hjorth, and Shape*).

For both classifiers, the results showed that using the basic group of features (i.e. average, standard deviation, maximum and median values) is the best configuration which reaches the higher values of all metrics. Moreover, incrementally adding new features to the basic group doesn't improve performance but, on the contrary, in each combination, a non negligible loss of performance was found. This demonstrates that, in this case, Hjorth parameters, Kurtosis and Skewness features do not add useful information content to the classification process.

Another parameter which characterizes the proposed methodology is the size of the time window on top of which to extract the classification features. In the scientific literature, there are various related studies that make use of time windows ranging from about 5 to 20 seconds. In this work, an in-depth analysis of the dependence of the performance of the classifiers on the time window size was carried out. Fig. 4 shows, for

Table 6
Neural network forward feature selection results

Features	Accuracy	Precision	Recall	F1score
B	0.9179 ± 0.0044	0.9083 ± 0.0059	0.8917 ± 0.0057	0.8992 ± 0.0053
H	0.8438 ± 0.0064	0.8004 ± 0.0095	0.8254 ± 0.0072	0.8127 ± 0.0081
S	0.7355 ± 0.0028	0.6453 ± 0.0047	0.6850 ± 0.0045	0.6646 ± 0.0038
B+H	0.8990 ± 0.0063	0.8791 ± 0.0065	0.8833 ± 0.0079	0.8812 ± 0.0069
B+S	0.8933 ± 0.0029	0.8656 ± 0.0039	0.8795 ± 0.0037	0.8725 ± 0.0035
B+H+S	0.8912 ± 0.0028	0.8620 ± 0.0068	0.8779 ± 0.0040	0.8698 ± 0.0036



(a) SVM (b) Neural Network

Fig. 4. Classification performances when varying the size of the time window.

both classifiers, the relation between the size of the time window and the performance metrics. Each point of the plots represents the average value, together with the standard deviation, calculated over a 5x2 cross validation test when varying the size of the time window. Both classifiers show the higher and stable performance for a window size ranging from from 7 to 12 seconds while, for shortest or longer time windows, the performances noticeably degrade while the standard deviations increase demonstrating a less stable results. In this work a time window of 10 seconds has been chosen as a good trade-off between classification performance and computational complexity (the smaller the time window, the higher the classifier execution frequency).

6. Conclusions

In this work we proposed a methodology based on machine learning techniques aimed at recognizing safe and unsafe driving behaviors by means of in-vehicle sensor data. In particular, starting from the signals captured through the OBD-II interface of the vehicle CAM bus, we computed a set of descriptive features capable to accurately describe the behavior of the driver. We also propose an objective method to label each driving time window as safe or unsafe starting from vehicle motion data according to the work presented by Eboli et al., 2016. Thanks to these generated labels two different classification tools, namely a SVM and a feed-forward neural network, have been trained and tested over on publicly available dataset containing more than 26 hours of total driving time spent by ten different drivers. The classification results show an average accuracy above 90% for both classifiers with a slight advantage (about two percentage point) of the neural network, demonstrating the potential capability of identifying driving styles by means of in-vehicle sensor data. On the other hand, the McNemar pairwise comparison test between the SVM and the neural network classifiers shows no significant difference on their classification accuracies with a confidence interval of 95% (p-value = 0.8479).

In our opinion, this study can give an active contribution in terms of improvement of road safety. In fact, it can pave the way for the development of very cheap devices, which, once connected the OBD-II port can alert, in real time, the driver in case of unsafe driving allowing him/her to take preventative measures. Moreover, one of the strengths of this method, unlike other approaches in literature, lies in the fact that it does not make use of any tracking system such as GPS, or of any recording device such a smartphone, to capture video and audio, which if incorrectly used could compromise the driver's privacy.

The proposed method could also represent a monitoring tool to obtain an overall judgment on the driving style of a person bringing benefits both, for obvious reasons, to the insurance companies, but also for the driver which can take advantage of new insurance paradigms such as the emerging "Usage-based insurance", where each driver pays in relation to how she/he drive.

Notice that, the best results were obtained using, as input features, the OBD-II compliant signals (i.e. vehicle speed, throttle position, engine speed, and engine load) together with non standard data such as braking system pressure and steering angle. Because the latter signals are not part of any standard, it is not guaranteed that these signals are always available for all cars.

The experiments conducted using only OBD-II compliant signals still show a noteworthy effectiveness of the proposed method (average accuracy above 84%) although a noticeable reduction in the precision and recall, related to the unsafe class, was measured (respectively 80% and 63%).

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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