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# Machine Learning Techniques in ADAS: A Review

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*Abstract*—**What machine learning (ML) technique is used for system intelligence implementation in ADAS (advanced driving assistance system)? This paper tries to answer this question. This paper analyzes ADAS and ML independently and then relate which ML technique is applicable to what ADAS component and why. The paper gives a good grasp of the current state-of-the-art. Sample works in supervised, unsupervised, deep and reinforcement learnings are presented; their strengths and rooms for improvements are also discussed. This forms part of the basics in understanding autonomous vehicle. This work is a contribution to the ongoing research in ML aimed at reducing road traffic accidents and fatalities, and the invocation of safe driving.**

***Keywords—ADAS; machine learning; supervised learning; unsupervised learning; reinforcement learning; deep learning***

## I. Introduction

Ever since the conduct of vehicular crash test, safety issues have been a major concern in the automotive domain [1]. In 2017 in the USA, over 37000 people died in road crash accidents [2] of which around 90% of accidents can be attributed to human errors [3], such as undetected risks or the driver's low reaction time. ADAS has indeed become indispensable for top car manufacturers so much so that each of them develop its own ADAS system. In general, a modern ADAS architecture [4] is composed of four main components, namely: *longitudinal control*, *lateral control*, *driving vigilance monitoring system* and *parking assistance*. The development and improvement of these systems are made possible through the application of machine learning techniques that are integrated into the system [5]. Machine learning, for itself, is the discipline that allows a machine to improve its performance by learning from previous events, in the same way that humans learn from experiences [6]. It can be divided into four main learning techniques, namely: *supervised learning*, *unsupervised learning*, *reinforcement learning* and *deep learning*. These techniques differ from each other on what and how the machine will learn. This paper briefly explains all these techniques and how they are associated with the ADAS components.

Nowadays, ADAS is a main research topic in the automotive research field [7]. Projects such as Tesla autopilot [8] or Google car Waymo [9] are sample achievements in this field and a testimony that it is still an unfinished task [10]. ADAS' current industrial implementation is restricted to high-end vehicles [11] in contrast to the main goal of this research, which is to implement ADAS in mid-range vehicles. A recent study performed by Bosch [3] showed that most drivers prefer to have ADAS systems in their future cars and 89% of them express the wish of having advanced features like automatic emergency braking for pedestrian or blind spot detection. In this survey, the aim is to conduct an analysis of recent works about machine learning application in ADAS [12, 13, 14, 15] . The work also highlights the strength of various works and put forward some suggestions for their possible improvements

## II. ADAS and Its Components

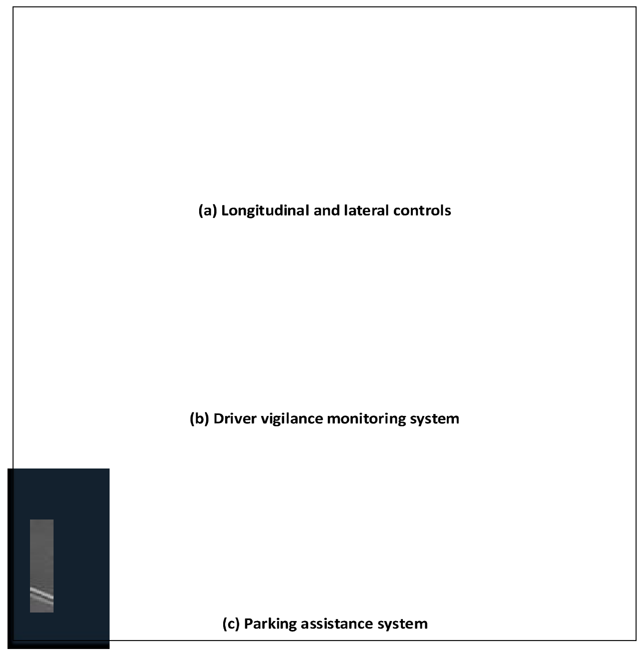


Fig. 1. Main components of ADAS, namely: (a) longitudinal control and lateral control, (b) driver vigilance monitoring system, and (c) parking assistance system.

### A. *Longitudinal Control*

In 1995, Mitsubishi [16] developed the first version of the preview distance control, the father of longitudinal control. It was a system that used sensor embedded in the car to measure the distance between two vehicles on the same lane. Nowadays, many mid-range vehicles [17] are implementing adaptive cruise control [18] and collision avoidance system [19]. These two systems allow the driver to be informed about dangers coming from the lane, control of vehicle's speed and evasive steering actions on the vehicle.

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## B. Lateral Control

The lateral control system is based on the same principle as that of longitudinal control: danger detection on the lateral lanes. Change lane and lane keeping are two systems serving this purpose. The former is an assistance related to detecting incoming vehicles or dangerous situations for lane change action [20]. The latter is based on the detection of sudden change of the vehicle's path with respect to the road lane [21], acting with warning messages. Future improvements include vehicle's evasive actions. An example of the area covered by lateral and longitudinal system control is shown in Fig. 1(a).

## C. Driving Vigilance Monitoring System

Distraction during driving is a major cause of accident especially for young drivers [22]. Driving vigilance monitoring system is one of the ADAS component that is still restricted to high-end car, such as the Mercedes-Benz attention assist system [23]. It consists of cameras and sensors embedded in the cockpit, monitoring in real-time the driver face and expression. The data are processed in order to evaluate driver emotions and important levels, such as stress, fatigue or anger.

## D. Parking Assistance

Parking assistance system's current state of the art is the most advanced one in terms of evasive action. Cars, such as the BMW x6 and Audi A8, implement auto-parking technology allowing it to enter in the parking spot without the steering action or presence of the driver. This is done with a camera in front and at the back of the car, together with the lateral and longitudinal sensors. Mid-range cars are still not implementing the evasive technology. To provide such functionalities, an intelligent vehicle makes use of several sensors and electronic systems to interact with the driver and the environment. Indeed, sensors like GPS, radar, lidars, accelerometer, wheel speed and steering angle in addition of automotive vision systems are deployed as an input or perception layer of a smart vehicle. The output comprises of the actuation or action layer whose role can vary from a simple notification to an alert or even to a direct reaction on the vehicle (i.e. braking, speed limitation) [24]. This work cannot be done without having an intelligent system equipped with machine learning algorithms capable of analyzing data and providing right decisions [25].

# III. MACHINE LEARNING AND ITS USE IN ADAS

Here, the different types of machine learning algorithms are presented, along with some known systems that use the learning techniques for a specific application in ADAS

## A. Supervised Learning

Supervised learning is based on the construction of an approximate model that can predict an output for new incoming data. It is based on the previous knowledge of output response to some inputs. An example is that of [6]. Consider, for example, a medical practitioner who wants to predict if a patient would have a cancer and if so whether this cancer would be benign or malignant. He can analyze the patient history and compare it to similar ones, going deep in the family's health history. At the end, he can have a model that predicts the possibility of the final scenario, giving a reasonable but uncertain result. A mathematical definition is given in [12]: given a certain number of inputs, usually called training set $X$, we have a corresponding value of the function $f$. The objective of the supervised learning is to find the best hypothesis $h$ that allows us to find a close value of $f$ for the given $X$.

Supervised Learning techniques are always a work of (i) *classification* and (ii) *regression*. The difference between the two is only on the input: discrete for classification while continuous for regression. Between the two, the former is made up of defined and finite number of values while the latter is composed of a range. In this ML category, the work of Patrick Tchankue et al. [12], Claire D'Agostino et al [13, 15], Yi Hou et al. [14] and Brendan Morris et al. [26] fit.

### A.1 Supervised Learning Applied in ADAS: "Using Machine Learning to Predict the Driving Context whilst Driving"

The basic idea of Patrick Tchankue et al. [12] work is the application of some supervised algorithms to create a model that predicts driver distraction and determine driving context. The input data set are through several sensors embedded in the mobile phone, such as accelerometer and GPS. All these data are managed by a mobile application, where the input data set is pre-processed and then sent to the learning algorithms. Once a model has been created, the best one is chosen and the final output is generated. The authors decided to apply many common supervised learning algorithms, such as J48, Bayesian network, logistic, naive Bayes, IB1, IBk and multilayer perceptron. Input data set was created through collaboration from five volunteers, who drove in a two-lane road turning two times left and right. The distance performed by all volunteers was 32.5 km. Fig. 2 shows a scheme of the work.

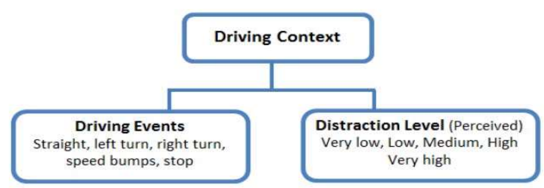


Fig. 2. Summarized scheme of Patrick Tchankue et al work

In this work, a good variety of the proposed algorithms allowed the authors to give a sufficient comparison scenario, achieving good results for some of the implemented algorithms: nearest decision tree gave 95.16% accuracy. One weak point is the limited number of distance performed by the volunteers and by consequence the limited input data set. Future improvement could be the implementation of a pre-processing phase on a bigger input data set, which would give a better model for the analyzed environment.

### A.2 Supervised Learning in ADAS: "Learning-Based Driving Events Recognition and Its Application to Digital Roads"

In this work [15], two machine-learning techniques are utilized for the creation of a classification model able to quantify the behavior of a truck, in particular on its fuel consumption. Input data set was created thanks to 11 drivers driving VOLVO trucks, which were equipped with controlled area networks (CAN). These networks collected data from embedded sensors, like speedometer, GPS, throttle and brake pedal percentage of pressure sensor. These data are then used in two learning algorithms: decision tree and linear logic regression classifier. The work's second part is an application on simulation. The database used in this work is composed of 11 digital roads of 5 km. The results show that the classification rates for urban, main road and highway classifications are around 80%, 81% and 90%, respectively with some misclassification on similar events.

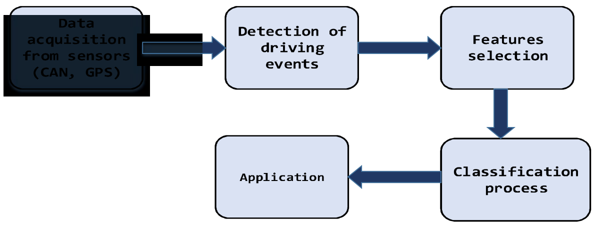


Fig. 3. Summarized scheme of D'Agostino's work

The use of three databases for the machine learning technique is an interesting aspect, but the small number of algorithms used gives it a limited vision of the environment. An improvement could be using other algorithms for classification task and then introducing a comparison of these algorithms choosing the best model that gives the best classification result.

*A.3 Supervised Learning in ADAS: "Modeling Mandatory Lane Changing Using Bayes Classifier & Decision Trees"*

In [14], Y. Hou et al. developed an assistance system for mandatory lane changes at drop lanes using a combination of two classifiers namely decision-tree and Bayes. The proposed classifier used a majority voting principal (to be considered, both Bayes and decision tree classifiers must predict the same event). The authors focused on non-merge events, giving higher misclassification cost on event that may result in traffic crash. The model was trained and tested using NextGeneration Simulation (NGSIM) data set. The prediction accuracy was 94.3% for non-merge events and 79.3% for merge events. The results show that the assignment of higher misclassification cost for non-merged events resulted in higher accuracy for non-merged events but lower accuracy for merge events.

*A.4 Supervised Learning in ADAS: "Lane change intent prediction for driver assistance: Design and evaluation "*

In this work [26], Brendan Morris et al. come up with a novel approach using Relevance Vector Machine (RVM), a Bayesian extension to SVM, to predict a driver's intention to change lane. To capture the driving context including that of the vehicle, the driver's state and the environment, two main categories of sensors were used: (i) radars such as Adaptive Cruise Control (ACC) to detect the different obstacles in front of the car and Side Warning Assist (SWA) to have a rear view, and (ii) cameras: one for driver head tracking and another for lane detection

Fifteen drivers were asked to perform a driving run in different driving conditions using a modified 2008 Volkswagen Passat equipped with the aforementioned sensors. This allows, along with other information captured by the vehicle's CAN bus, the generation of over 200 signals. The resulting dataset contained about 15.5 hours of driving data. The use of RVM helped in selecting the most relevant features among the 200 signals and therefore allowed fast computation in real time. The proposed system was capable of predicting lane changing up to 3 seconds ahead of time. Yet, the results obtained can be improved by addressing the reasons for false positives such as events approximating lane changes (i.e. merges, exits).

*B. Deep Learning*

Deep Learning is an approach to artificial intelligence (AI) based on the creation of several layers, with a final graph characterized by a depth [27]. Generally, deep learning techniques use artificial neural network (ANN) in order to create and represent the model. An ANN is always composed of an input layer and an output layer, but between them, several intermediate layers will implement the deep learning algorithm. Deep learning finds its application in speech recognition, object classification and detection, pattern recognition, robotics and self-driving cars to name a few. Even though Deep learning requires huge training datasets and heavy computational capacities, it is considered as one of the best choices for real time inference [28]. There are three main models in deep learning which are Recurrent Neural Networks (RNN), Convolutional Neural Networks (CNN) and Deep Belief Networks (DBN) [29].

In the world of image processing, deep learning plays a key role. The ability to represent images by means of multiple hidden-layer neural networks allows clear analysis of key parts of an image. It is for these reasons that the driving vigilance monitoring system is based on deep learning techniques, with the usage of cameras pointing to the driver's face. Deep learning is also used for obstacles, road lanes and pedestrian detection [30,31,32,33] and it is mainly based on computer vision models.

*B.1 Deep Learning Applied in ADAS: "Deep Learning for Target Recognition from SAR Images"*

Ali El Housseini et al. [34] proposed a deep learning application that recognizes military vehicles from synthetic aperture radar (SAR) images. This work is based on the use of CNN and convolutional auto-encoder (CAE) algorithms together in order to achieve good image recognition accuracy. While the former is used as a deep learning approach, the latter is an unsupervised one, used as data pre-processing phase. In fact, CAE is often used for extracting features from raw data to yield a structured data as input for other machine learning applications. In this work, the authors used as input a dataset that involves ten different tank targets, taken from MSTAR that contains 3887 images. To validate the accuracy and reliability of the algorithm used, they also applied CNN without the pre-processing phase made by CAE. In the result's analysis, they showed that CNN method took 8.14 x $10^{-4}$ seconds to recognize one image against 30 x $10^{-6}$ seconds for the combination of CAE and CNN. A summary scheme in Fig. 4 explains how the work is organized, illustrating the two used paths for image recognition.

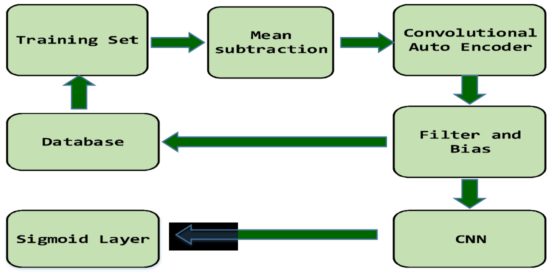


Fig. 4. Summarized scheme of Ali El Housseini et al work

The work shows good accuracy results, with a mean of 92.74% of image recognized, which explains why a good pre-processing phase made by feature extractions is a key point in deep learning application. For further improvement, the authors could have added more deep learning algorithms in order to evaluate the reliability of the one they used; they can also increase the number of images analyzed for better accuracy.

*B.2 Deep Learning Applied in ADAS: "Deep Learning in the Automotive Industry: Applications and Tools"*

This article [35] is a good example that shows the impact of big data in the machine-learning universe, especially in the automotive field. Big data tools, such as Hadoop and Spark [36], were used to process the input data set, taken by ImageNet. In addition, the authors also created a visual inspection process, yielding a total number of 82011 images. The model training chosen were AlexNet and GoogLeNet that are based on graphic process unit (GPU). The key contribution of this article is the combination of deep neural network and big data. In conclusion, the work exhibits the deployment of the models used using a mobile application. This application, built to provide support to the processing and improve data collection, also integrates the trained network. The introduction of the pre-processing phase based on big data tools lead to good results: 85% of the images were correctly classified. The use of real-world data, the creation of its own data set and the good amount of images processed are the strong points of this article, whose mobile application utilization reinforces its reliability.

*B.3 Deep Learning Applied in ADAS: "An empirical evaluation of deep learning on highway driving"*

Huval et al. in [32] proposed a model based on a Convolutional Neural Network (CNN) for real time detection of lanes and cars in highways. To train the model, the authors built a dataset of over 630000 images of vehicle bounding boxes and lanes annotations. The dataset was obtained using a 2014 Infiniti Q50 equipped with camera, lidar, radar and GPS. An image resolution of 640 × 480 was chosen to allow the system to detect cars at more than 100 meters away. To consider the driving constraint in a highway, the system was designed to operate at a frequency of over 10 Hz. Fig. 5 presents an example of an output of the system.

Even though the model was capable of identifying cars 60 meters away with 95% accuracy at a frequency of 44 Hz, it still suffers from some failures caused by objects having shadowing effects like overpasses and trees.

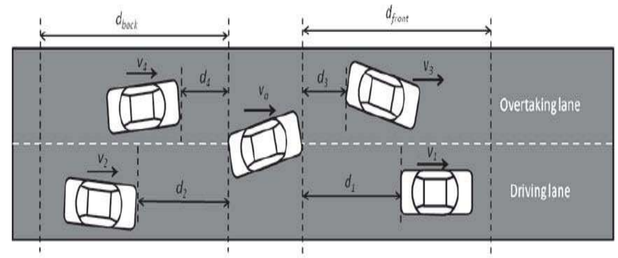


Fig. 5.Summarized scheme of Xin Li's work.

*B.4 Deep Learning Applied in ADAS: "Real-Time Rear-End Collision-Warning System Using a Multilayer Perceptron Neural Network"*

In [37], Donghoun Lee et al. proposed a system meant for real-time Collision Warning based on a Multi-Layer Perceptron Neural Network (MLPNN), named MCWA (MLPNN-based rear-end collision Warning Algorithm). The input layer was composed of five input neurons: the distance between preceding and following vehicle, the speed and acceleration of the following vehicle, and the speed and deceleration of the preceding vehicle. The final output used a threshold discriminator of 0.5 to come up with a value of 0 or 1, indicating whether a rear-end collision warning should be displayed. Likewise, learning algorithm convergence was enhanced using momentum method for weight updating. Even though the authors claimed superiority of the model in predicting rear-end collision compared to others TTC (Time To Collision) algorithms (Berkeley and Honda algorithms), the performance of the model is yet to be compared with other traditional machine learning classification methods such as Support Vector Machine, Random Forest, Decision Tree, and Naïve Bayes.

*C. Reinforcement Learning*

Reinforcement learning is a particular area of machine learning that is based on taking some actions, followed by numerical rewards [38] to attain an objective. The important point is that the one who takes action, named agent, in a particular ruled world, named environment, does not know which action is good or bad, but he/she will learn which ones will give the highest rewards $r$ by trying them. In addition, a policy $p$ is defined as the path of action that leads to a solution. From a mathematical side, reinforcement-learning problems are always modeled as Markov decision process (MDP) [38]. Markov decision process provides the mathematical rules for decision-making problems, both for describing them and their solutions. Consider the parking action: this could be thought as an MDP. The environment would be the parking spot; the agent will be the system that acts on the wheel and the reward is linked to the correct positioning of the car, the state. Actually, reinforcement learning is used mainly for parking assistance, but in the future, it would be utilized also for evasive steering actions.

*C.1 Reinforcement Learning Applied to ADAS: "A Decision-Making Method for Autonomous Vehicles based on Simulation and Reinforcement Learning"*

Rui Zheng et al. work [39] shows how and why reinforcement learning could be the key in solving the decision-making system for complex traffic conditions design problem. In this article, the authors proposed a 14-degree of freedom (DOF) model for simulating their decision-making method. This model is composed of three parts, each one taking into account one part of the modeled car: steering system model, body and suspension model, and motion model. Accelerating and breaking models were gathered from data-driven method. Models output is used as dataset input for the decision-making system which was modeled as a Markovian decision process. Then, the authors applied the least square policy iteration (LSPI) method [40] to settle the MDP for autonomous vehicle problem. The testing phase shows that the simulation model follows the real characteristics of the vehicle and, most importantly, the decision-making process using reinforcement learning correctly fixed the problem. Possible improvement could have been made in applying the decision-making system to a real case, also adding a pre-processing phase that would involve the correct classification of the raw collected data. The application on a complex highway situation is a strong point of this article, showing the way ADAS and reinforcement learning applications are related to one another.

*C.2 Reinforcement Learning Applied to ADAS: "Reinforcement-Learning Based Overtaking Decision-Making for Highway Autonomous Driving"*

Xin Li et al. work [41] is the continuation of the work of Zheng et al. [39]. This work improves the previous one in the implementation of overtaking policies, learned by reinforcement techniques, and by adding different driving scenarios. The algorithm used for solving the MDP process is called the Q-learning. The input data set is composed of the output of 14-DOF dynamic model already presented in [40]. The final application is to learn a vehicle overtaking position's average speed and the distance between the vehicles present in the other lanes. The key aspect of its contribution is the presence of a simulation phase useful to show different driving scenarios: a need to overtake due to slow speed of a vehicle ahead on the same lane or choosing the lane after an overtake. Equation 2 shows the reward function used by the authors, who used five different aspects for giving rewards: (i) Lowest reward is given if a collision occurs; (ii) Sudden change in velocity produces penalty; (iii) Staying in overtaking lane gives lower reward than staying in driving lane; (iv) If the vehicle is too fast, deceleration action gives high reward and (v) In overtaking phase, vehicle speed should stay at a determined value.

$$r^{(k)} = \begin{cases} -300 & c=1 \\ -150 & c=0\&v_d^{(k)}>10 \\ -0.1v_d^{(k)} & c=0\&v_a>v_f \\ v_a^{(k)}-v_f^{(k)}-0.1v_d^{(k)} & c=0\&l=2 \\ v_a^{(k)}-v_f^{(k)}-0.1v_d^{(k)}+(d_1-v_1) & c=0\&l=1 \end{cases} \quad (2)$$

where $r^{(k)}$ is the reward given at $k$ step, $l$ is the current line number, $v_a$ is the vehicle speed, $v_d$ is the velocity difference between final moment and current one, $v_f$ is the expected upper limit of $v_a$, while $d_1$ and $v_1$ are distance between vehicle $1$ and the autonomous one and velocity of vehicle one, and $c$ is the detector of collision.

The simulation phase and the 14-DOF model created by the author gave this work sufficient reliability and role in the current state-of-the-art. A possible improvement of this work could be the implementation of the trained model in the real world as well as the collection of vehicle data in real time using embedded sensors. The author could also have implemented more learning algorithms, adding a comparison phase in order to have the possibility of opting for the best result for the final output computation.

*D. Unsupervised Learning*

Unsupervised learning is characterized by the absence of an exact knowledge of what data contains or what is the final goal [6]. This is also its main difference with supervised learning, where one can predict a known response. It is due to the lack of fixed labels that it is not possible to evaluate its result. In unsupervised learning, what the machine is going to learn is how to cluster data and try to describe what is inside them, even if one does not know exactly how they are structured or what they contain. From a mathematical point of view, the training set $X$ does not have a known output value (function $f$) [42] and the final goal is to try to create one.

An example of what unsupervised can do is to describe what there is in a crossroad: traffic lights, vehicles, people and so on. One can also try to divide and cluster different kinds of vehicles: bicycles, cars, bus. The key point is that one does not know in advance what the crossroad contains; one just sees that all the vehicles have different characteristics with respect to people. For example, they move at different speeds and just by being on the road, one decides to call them vehicles without really knowing what a vehicle is because it is only one of the possible method of classification. It is due to all of these considerations that we talk about feature extraction when applying an unsupervised algorithm: one finds unseen patterns or labels, extracting common features on individuals that are being considered. Looking back, the ability to move is a feature for both vehicles and people that distinguish them from the traffic lights; it can also be a feature that allows us to segregate them into two different clusters [43].

With the recent assent of big data [44, 45], feature selections has become a key phase in machine learning applications, as in the case of Arash Jahangiri and Hesham A. Rakha work [46], that of C. Miyajima et al. [47] or the work of Ravi Bhoraskar et al. [48]. Unsupervised learning finds its main application in the pre-processing phase of other machine learning methods, especially in feature extraction. Big data is usually identified with the three v's – variety, velocity and volume. Unsupervised learning is a key tool for managing these problems, thank to its ability to manage tremendous amount of raw data. It is for this reason that it is mainly used with supervised learning in the lateral and longitudinal control systems, managing all the sensors input data set.

*D.1 Unsupervised Learning Applied in ADAS: "Applying Machine Learning Techniques to Transportation Mode Recognition Using Mobile Phone Sensor Data"*

This Jahangiri and Hesham A. Rakha [46] work made use of phone sensor's data to determine the mode of transportation, such as taking a car, riding a bicycle or running. The authors built a model that classifies and distinguishes the transportation means. This work proposes five different supervised algorithms [46, 49] such as support vector machine (SVM) and decision trees for the classification, preceded by a pre-processing phase of feature selections. Unsupervised methods were applied because of the huge amount of raw data with undetermined events. Experiments were conducted on 10 employees of Virginia Tech Transportation Institute, and everyone used the application for 30 minutes. Features selection was a critical and fundamental step because there were no particular restrictions on the trips that they should have performed. Fig. 6 shows the proposed conceptual scheme, underling the importance of features selection phase that allows conversion from 165 features to 80 most useful ones.

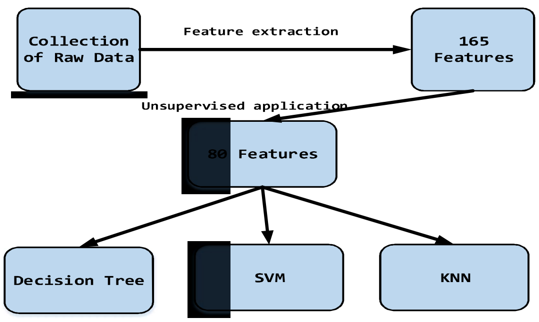


Fig.6. Conceptual diagram of Jahangiri and Hesham A. Rakha work.

The authors used decision tree and SVM as main algorithms and k-Nearest neighbor (KNN) as a comparator so as to validate the reliability score. The authors have decided to collect data in the most natural way, leading them to misclassify some results, especially in distinguishing between similar means of transport like bus and car. However, they performed a significant pre-processing phase, due to the naturalness of the collected data. One of the possible main improvements, also proposed by the authors, could be increasing the number of collected data to reduce the misclassification percentage.

*D.2 Unsupervised Learning in ADAS: "Driver Modeling via Driving Behavior & Evaluation in Driver Identification"*

The idea of this work [47] is the creation of an approximated model for evaluating the vehicle's optimal speed, using analysis of the distance between two vehicles moving on the same lane and their speeds. In addition, a second model is created for mapping the relationship between break and gas pedal. In both cases, Gaussian mixture model (GMM) [50] was used except that in the former case, the author added non-linear function analysis. The two models were used in 276 different real-world scenarios; the data collection was taken from 20 volunteers that drove car in a simulated environment for 20 minutes. Fig. 7 shows the different signals collected by the car environment simulator.

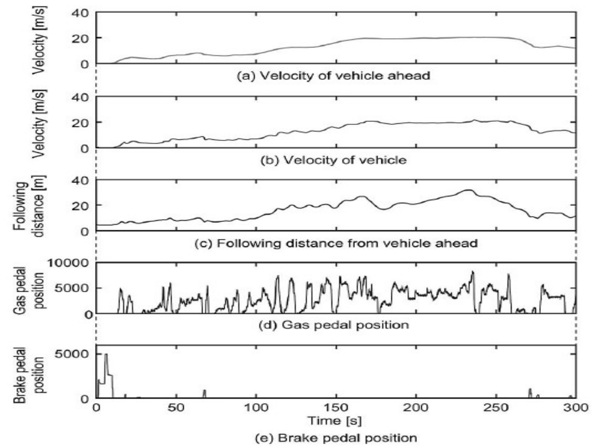


Fig.7. Driving behavior signals collected in a driving simulator

*D.3 Unsupervised Learning in ADAS: "Wolverine : Traffic and Road Condition Estimation using Smartphone Sensors"*

In [48] Ravi Bhoraskar et al. proposed a method called *Wolverine* to detect road and traffic conditions using a smartphone equipped with magnetometer, GPS sensor and accelerometer. Authors started by proposing a novel algorithm to align the smartphone with vehicle axis by reorienting the three-axis accelerometer. They focused then on the detection of two events i.e. braking, as an indicator of jammed traffic, and bump as a road state indicator. To do so, they used an unsupervised algorithm i.e. k-means clustering algorithm (with K=2) to classify the sensor data into two categories for each event, namely bump and brake. Data was manually labelled as either smooth/bumpy for the former category or brake/not brake for the latter one. This work was performed as a pre-processing phase. For braking detection, the model shows 21.6% false negative rate and a percentage of 2.7% false positive whereas, for bump detection the rate was 10% false negative. We can conclude that even though wolverine system gave very good results regarding false positives in both cases, it can be improved in terms of false negative rate by applying more advanced machine learning algorithms.

## IV. CONCLUSION

In this work we have analyzed the most important machine learning techniques and ADAS components, in order to create a relationship between them. The contribution and goal of this paper is to give the readers a good grasp of possible applications of machine learning in ADAS, at present and in the future. We have seen that supervised learning can be associated with longitudinal and lateral controls, since they used data coming from sensors in order to create a model for detecting danger or ensure safe driving situations. Unsupervised learning is used mainly as a preprocessing step, transforming sets of raw data into classified ones. For this reason it fits mainly for longitudinal and lateral control, but could play a key role in the image processing application, like driving vigilance monitoring system. Reinforcement learning can be applied to every ADAS components implementing a decision-making method. At the current state-of-the-art, we have a complete application for parking assistance system, but in the future, it will be applied in autonomous driving scenario, including evasive actions on the steering wheel performed by longitudinal and lateral control systems. Deep Learning finds its main usage in the image processing world, thanks to the creation of complex multi-layer neural network. In ADAS, it is associated with driving monitoring system in the recognition of stress and fatigue levels, monitoring and analyzing continuously the driver face. It also plays a role in the parking assistance system, giving a general view of the environment in which the reinforcement learning plays a role. The analysis of the related works was conducted in order to find and underline strength and points for improvements, relating them to the current state-of-the-art in this field. Future works in ADAS and autonomous driving will be more and more related to machine learning methods. This survey is useful for researchers who wish to have a general view both on machine learning and ADAS worlds, and on the association and relation between them.

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TABLE 1. DIFFERENT ADAS WORKS AND THE MACHINE LEARNING TECHNIQUES USED

| Machine Learning Type | Research/Practical Work | ADAS Type | What was done? | How it was done? | Result |
|---|---|---|---|---|---|
| **Supervised Learning** | "Using Machine Learning to Predict the Driving Context whilst Driving" by Patrick Tchankue et al. [7] | Lateral and longitudinal control | Modeling of driving context and detection of driver distraction. 5 volunteers drove for 6.5 km on a two-lane road. Data collected via mobile phone with sensors. | Input data are pre-processed in the mobile application, then learning algorithms are applied. The output of the algorithms is evaluated and the best model is chosen for the final output. | Accuracy of 95.16% for the model of driving context |
| | "Learning-Based Driving Events Recognition and Its Application to Digital Roads" by Claire D'Agostino et al. [17] | Lateral and longitudinal control | Recognition of different driving events. 11 pilots drove Volvo trucks in order to collect data. | Data were collected by means of CAN and GPS signals. After the learning phase, by means of algorithm like decision tree, the simulation phase takes action. | 80-90 % of driving events recognized |
| **Deep Learning** | "Deep learning in the automotive industry: Applications and tools" by Andre Luckow et al. [30] | Driving vigilance monitoring system | Creation of an automotive dataset for detecting vehicle property and a mobile application for data collection. | Use of big data tool to create datasets. 82,011 images were collected and processed using CNN to learn a model of different vehicle properties. | Using real-world data, the model was able to recognize about 85% of the images |
| | "Deep Learning for target recognition from SAR images" by Ali El Housseini et al. [29] | Driving vigilance monitoring system | Images processing for recognizing military vehicles classes Images were taken using SAR. | 2 different approaches: first, the authors pre-processed the data and then applied CNN based algorithm, and next, they used the CNN-based approach. 3887 images were analyzed. | A global 92.4% for the CAE/CNN method were achieved. The CNN based approach took $8.14\times10{-}4$ seconds to recognize one image, against $30\times10{-}6$ seconds taken combining CAE and CNN. |
| **Reinforcement Learning** | "A decision-making method for autonomous vehicles based on simulation and reinforcement learning" by Rui Zheng et al. [34] | Parking assistance | Creation of a system for autonomous vehicle, able to make decision in a highway traffic scenario. | A 14-DOF dynamic model was created to represent the autonomous vehicle. The model output was used to create the MDP, solved by applying a LSPI algorithm. | The decision-making model developed was able to find the policy for the MDP. |
| | "Reinforcement learning based overtaking decision making for highway autonomous driving" by Xin Li et al. [35] | Parking assistance | Application of the developed model in [33] for learning overtaking decision process. | Monitoring vehicle speed and minimum distances between vehicles, the MDP was based on overtaking decision process. Q-algorithm was used for different traffic conditions. | Simulation showed that the model was able to learn different policies and perform better than before the learning phase. |
| **Unsupervised Learning** | "Applying Machine Learning Techniques to Transportation Mode Recognition Using Mobile Phone Sensor Data" by Jahangiri [39] | Longitudinal and lateral control, driving monitoring system | Recognition of the transportation mode: car, bicycle, running, bus. Data collected driving for 30 minutes, 10 volunteers. | Phase of feature extraction and features selection by means of unsupervised methods. Then, 3 different supervised algorithms are applied. | Features reduction from 165 to 80. |
| | "Driver Modeling Based on Driving Behavior and Its Evaluation in Driver Identification" by Chiyomi Miyajima et al. [40] | Longitudinal and lateral control, driving monitoring vigilance system | Creation of 2 models: one for the optimal speed, the other for map brake and gas pedal relationship. Data collected from 20 volunteers driving for 20 minutes following a vehicle without passing it. | Usage of a combination of GMM and non-linear function for the creation of the approximation model of the optimal-speed. For the gas-brake pedal relationship only GMM was used. | 89.6% for the driving simulator and 76.8% for the field test with 276 drivers. |