# Car Safety Support System on the Base of Data Mining Algorithm 

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#### Abstract

According to the target of the $11^{\text {th }}$ Sustainable Development Goal, to reach sustainability in cities, we have to ensure the transport systems' safety. Since safety driver assistance systems play a critical role both in averting crashes and reducing the likelihood of serious injury, we suggest a Safety Support System based on machine vision and a data mining algorithm that could be used for application to decision module of fully- or semi-autonomous vehicles. The created system was tested on a simple collection of photos from a Polish two-lane road. The novelty of this system is concluded in our EAV (Entity-Attribute-Value) model based algorithm that, while providing the same level of accuracy, works faster by reducing the number of analyzed attributes.


Keywords: decision making algorithm, decision rules, autonomous driving, ADAS, sustainable transport, EAV model, decision table, machine vision, objects detection, image recognition, road safety.

## 1. INTRODUCTION

In 2015, at the United Nations Headquarters meeting in New York, Heads of State and Government and High Representatives have adopted a historic document titled the 2030 Agenda for Sustainable Development [1], where was presented a decision on a comprehensive, farreaching and people-centred set of universal and transformative Goals and targets, so-called Sustainable Development Goals (SDG). In the 2030 Agenda, sustainable transport is mainstreamed across several SDGs and targets, especially those related to food security, health, energy, economic growth, infrastructure, and cities and human settlements. Subsequently, the UN Secretary-General, as part of his Five-Year Action Agenda, identified transport as a major component of sustainable development [2]. The pandemic of COVID19 also has drawn attention to the need for safe, accessible and reliable transport [3]. But what is it sustainable transport? According to the SDG 11.2, by 2030, there have to be provided an "...access to safe, affordable, accessible and sustainable transport systems for all, improving road safety...". This means that one of the ways to reach this goal is to improve transport safety.

Today there are a lot of scientific researches prove that the great number of road accidents are connected with the violation of traffic rules and slow or incorrect
drivers' reaction to some dangerous situations, i.e., due to "human factor". For example, Zhang et al. have showed in their article [4] that unsafe behaviour of road users is the most frequent reason of road accidents. Under the "unsafe behaviours" can be understood such reasons of road accidents, as alcohol intake [5], high driving speed [6], and even drivers' emotional status [7]. Therefore, there is a widespread opinion [8] that introduction of fully- or semi-autonomous vehicles into the road traffic will improve road safety and, as a result, sustainability of the whole transport system. However, appearance of autonomous vehicles by itself is not a panacea for traffic accidents. New types of vehicles with fundamentally new control systems may induce new types of errors causing new, not existing now, safety problems [9]. Therefore, it is very important to analyse possible risks of autonomous driving introduction and to identify steps that can prevent them or mitigate their consequences. Authors of the research [10], list potential risks accompanying transport system's intellectualization. From our point of view, the main safety problems that can appear after wide integration of autonomous vehicles are:

1. cyber-attacks;
2. mistakes in objects recognition and overall ,,understanding" of the situation on road;
3. complexity of the decision-making algorithms;
4. increased requirements to communication systems;
5. increased requirements to information processing speed.

This means that despite digitalization and intellectualization provide increased efficiency, safety and sustainability of complex systems [11], road safety will depend on intelligent algorithms for decision making: on their correctness, speed, completeness of the knowledge database and the possibility of self-learning.

Today, the world's leading automotive producers develop Advanced Driver Assistance Systems. Such systems include, for example, an electronic engine management system, a remote vehicle diagnostics system, safety systems, vehicles' positioning and a number of others [12, 13]. One of the important areas of vehicle intellectualization is accident prevention systems based on "machine vision". For example, Mobileye [14] is being developed today, which is used in BMW and Tesla cars. As the leader in automotive safety, Volvo also couldn't avoid developing its own technology City Safety [15]. The first generation of standard brake support Volvo has introduced in 2006. Now, City Safety takes on an extended, all-new role in car brake solution: it is efficient at all speeds including slow-speeds from $4 \mathrm{~km} / \mathrm{h}$. Subaru also has its own Driver Assist Technology: EyeSight. When equipped with EyeSight, the 2019 Ascent, Crosstrek, Forester, Impreza, Legacy, Outback, and WRX received the highest possible rating for front crash prevention from IIHS highest rated claim from 2019 to 2020 [16].

Cross Traffic Alert Systems [17] also help to prevent many accidents when the driver does not notice traffic
moving in a cross direction. Such systems are usually based on high frequency radars ( 20 GHz and higher) However, they are quite expensive and can be installed in high-end vehicles as an additional option [18]. Machine vision can greatly simplify such systems and make them widely available
the machine vision is not only the image recognition, it is mostly about automation of understanding of what machine "sees" in this world and decision taking basing on it. Therefore, artificial intelligence (AI) algorithms should be used by the machine to perform a problemsolving function. In transport, intelligent systems based on machine vision are used to solve such problems as: road safety analysis [19], intelligent traffic control at intersections [20], objects tracking [21], obstacle detection and navigation [22], crash prediction [23] etc.

In the machine vision systems, the design of AI algorithms is an important part of the decision making based on real-time information. It requires to be efficient in terms of time required to process the algorithm for a large number of input data. That is why, despite a lot of different researches are made on the development of different AI decision making algorithms, there are still a lot of work to be done in order to make these algorithms work faster and more accurate.

## 2. MATERIALS AND METHODS

We suggest that the Safety Support System in the fully- or semi-autonomous vehicles should have 3 modules:

1. Object detection module,
2. Data analysis module,


Figure 1 Snippet of the Object detection module's libraries.

PRESS
3. Knowledge database founded on the algorithm for decision rules generation.

### 2.1. Object Detection Module

The process of image recognition is based on the RetinaNet model. This model was chosen because according to the researches made by Saini et al. [24], Fan et al. [25], Carranza-García et al. [26], RetinaNet is highly accurate, especially for unmanned aerial vehicle (UAV) technologies. Our object recognition model has been trained with the help of the COCO collection [27].

The created Object detection module is implemented in Python and it allows detecting 80 different objects from everyday life in the images in jpg format. The outcome of the module are the photos with information about the detected object and the probability with which this object was detected. Additionally, the detection result is displayed in the console from which the script is run. It is a single script application which code is presented in Figure 1.

### 2.2. Data Analysis Module

To create this module, the field expert is responsible for building a Decision Table based on previously received information on objects detection. This Decision Table should contain criteria to classify the objects detected on the images into suggested groups (in our case - to specify the number and probability level of recognised cars and trucks). Probabilities of belonging to
a particular group must be discretized (it is necessary to generate decision rules in the next step). Role of the field expert is to define actions (based on a given photo) that autonomous vehicle can perform in a given situation for road traffic safety. Thanks to this, it is possible to perform a supervised learning of the model, which, in principle, will assist in driving an autonomous vehicle.

### 2.3. Knowledge database built on EAV model based algorithm

On the base of the Decision Table from the Data analysis module, the Knowledge base was generated automatically. This module is processing according to the EAV (Entity-Attribute-Value) model based algorithm that belongs to the group of heuristics as it constitutes approximate decision rules. We have developed this algorithm to reduce the number of attributes under consideration while getting the same level of accuracy. In our previous articles [28, 29], we have compared results of our algorithm with the results provided by the use of dynamic programming approach.

To ensure road traffic safety in the future, when autonomous vehicles will become usual road users, it is extremely important that they make decisions as quickly and correctly as possible. This will highly depend on the quality of the decision taking algorithms. That's why we suggest to use our EAV model based algorithm that, while providing the same level of accuracy, works faster by reducing the number of analyzed attributes.

The algorithm consists of the following steps:


Figure 2STD of the decision algorithm based on EAV model.

1. Selection of the best attributes from the Decision Table based on their distribution (standard deviation) in relation to the decision class.
2. Generation of the decision rules consisting of the best attributes that have been chosen in the selection step (the generated rules are optimal in terms of length).

We have created the state transition diagram (STD) to show our algorithm [30] (Figure 2). We believe that this algorithm still can be developed, and we will continue working on it in our future researches.

One more advantage of our suggested algorithm is that the Knowledge database generated in this way can be easily enlarged with new rules. Moreover, the set of rules can be not only infinitely extended, but it also can be updated. This helps to avoid the Knowledge base becoming too large, so that it is able to be used in real time and is easily maintainable. This means that it will be a Self-Learning System that can be used in autonomous vehicles.

## 3. RESULTS AND DISCUSSION

To check the proposed approach and to start building the Decision Table on the base of the real data, we have carried out experiments based on a series of frames collected from a fragment of a dashboard camera's recording from the Polish two-lane road.

The first step is the image recognition using the proposed Safety Support System. We have taken as an example only 9 photos, however, the system will be able to extract 30 frames per one second of the video [31]. In the Figures 3-11, objects were identified, classified and they contain the probability (expressed as a percentage) with which the object has been detected as a car or a truck.


Figure 3 Objects identified in the $1^{\text {st }}$ photo.


Figure 4 Objects identified in the $2^{\text {nd }}$ photo.


Figure 5 Objects identified in the $3^{\text {rd }}$ photo.


Figure 6 Objects identified in the $4^{\text {th }}$ photo.


Figure 7 Objects identified in the $5^{\text {th }}$ photo.


Figure 8 Objects identified in the $6^{\text {th }}$ photo.


Figure 9 Objects identified in the $7^{\text {th }}$ photo.


Figure 10 Objects identified in the $8^{\text {th }}$ photo.


Figure 11 Objects identified in the $9^{\text {th }}$ photo.
Based on the results of the objects detection, an exemplary Decision Table was created (Figure 12). It has been built manually basing on opinion and experience of the expert who knows which factors are influencing the decision taking while driving. In our further researches we will enlarge, correct and verify this Decision Table by opinions of other experts in order to build the Intelligent Self-Learning Expert System later.

Taking into account the results of object detection, it is possible to distinguish several attributes that can affect driving the vehicle. They are:

- number of identified cars;
- number of identified trucks;
- maximum probability for this object that it is a car;
- maximum probability for this object that it is a truck.

To apply our decision rule generation algorithm, these probabilities had to be discretized (they have been grouped into 10 intervals consisting of 10 percentages each: 0-10, 10-20, 20-30, 30-40, 40-50, 50-60, 60-70, 7080, 80-90 and 90-100).

The Decision Table is used to create a Knowledge Database consisting of decision making rules constructed using our EAV model based algorithm. The set of decision rules is presented in Figure 13.

On the base of experiments made, we can say that the proposed decision rules are optimal with respect to the length (in relation to the Decision Table row for which they have been generated). Since the algorithm can generate same rules for different Decision Table rows, we have removed duplicated ones. A Knowledge Database constructed in such a way can be directly integrated into an autonomous vehicle control module and additionally freely expanded according to changing needs.

| Number of cars <br> (no_of_cars) | Number of trucks <br> (no_of_trucks) | Maximum probability <br> for the car <br> (max_car_propability) | Maximum probability <br> fort the truck_probabality) | Proposed action <br> (action) |
| :---: | :--- | :--- | :--- | :--- |
| 1 | 1 | $70-80$ | $70-80$ | accelerate |
| 4 | 1 | $80-90$ | $90-100$ | neutral |
| 3 | 1 | $90-100$ | $70-80$ | neutral |
| 2 | 2 | $90-100$ | $60-70$ | neutral |
| 3 | 1 | $90-100$ | $50-60$ | brake |
| 2 | 0 | $90-100$ | 0 | brake |
| 2 | 0 | $90-100$ | 0 | brake |
| 2 | 0 | $90-100$ | 0 | brake |
| 1 | 0 | $80-90$ | 0 | stop |

Figure 12 Exemplary Decision Table for the set of identified objects.

Decision rules of the form (attribute=value) $\rightarrow$ decision
( no_of_trucks = 1)( max_truck_probability $=70-80$ )(no_of_cars =1) $\rightarrow$ accelerate ( no_of_trucks = 1) ( max_truck_probability = 90-100) -> neutra ( no_of_trucks $=1$ ) ( max_truck_probability $=70-80$ ) (no_of_cars $=3$ ) $\rightarrow$ neutral ( no_of_trucks $=2$ ) $\rightarrow$ neutral
( no_of_trucks =1)( max_truck_probability $=50-60$ ) $\rightarrow$ brake
( no_of_trucks $=0$ )( max_truck_probability $=0$ )(no_of_cars = 2 ) -> brake
( no_of_trucks $=0$ ) ( max_truck_probability $=0$ )(no_of_cars $=1$ ) $>$ stop
Figure 13 The exemplary set of generated decision rules.

## 4. CONCLUSION

According to statistics published already in 2015 [32], the use of Automated Emergency Braking System can reduce the number of collisions caused by too close approach of the car to the car in front. Moreover, the use of machine learning can greatly simplify such systems and make them widely available.

We suggest a Car Safety Support System based on machine vision and consisting of: (1) a subsystem recognizing objects on photos with a certain probability; (2) a Decision Table formed by the field expert; however, in the future, it will be extending on the base of "road experience" of this self-learning system; and (3) a knowledge database built on decision rules generated with the help of our EAV based model data mining algorithm.

The next steps of our research are to develop the decision taking algorithm so that it worked even faster and to create the Intelligent Self-Learning Expert System based on several high quality field experts' opinions.

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