# The usefulness of Artificial Intelligence in safety assessment of different transportation modes

**Dimitrios I. Tselentis[1]*, Eleonora Papadimitriou[1], Pieter van Gelder[1]**

[1]*Faculty of Technology, Policy, and Management, Safety and Security Science Section, Delft University of Technology, Jaffalaan 5, Delft 2628 BX, the Netherlands*

## 1. Introduction

AI is a subpart of computer science, concerned with how to give computers the sophistication to act intelligently, and to do so in increasingly wider realms [1]. AI leverages computers to mimic the problem-solving and decision-making capabilities of the human mind. ML is a branch of AI that develops algorithms imitating human way of learning and gradually improve prediction accuracy. A part of AI algorithms that imitate the brain's structure and function using ANN, is Deep Learning. Over the past decades, a rapid technological progress is witnessed, especially in telematics, Internet of Things (IoT), Internet of Vehicles (IoV) and Big Data (BD) analytics. The adoption of technological advances in sensor devices, such as autonomous vehicles (AV), is widespread because they present many advantages due to high market penetration rates, and IoT and IoV connectivity.

Transportation systems are complex systems involving a very large number of components and different parties, each having different and often conflicting objectives. Regarding transportation safety problems, the focus is on the intelligent systems related to accident prevention and severity mitigation, accident modelling, accident frequency analysis, human factors, risky driver/operator behaviour, automatic incident detection and monitoring, obstacle detection, with the aim to decrease the number of accidents for transportation users [2]. The interest into ML and AI to solve the aforementioned problems is increasing among transportation researchers and practitioners during the last decades as we are moving into an era of significantly higher computational power [3].

Historically, safety models were developed based on collision records stored in databases. The most recent interest in developing collision models and performing safety analysis is based on actual observations of precursors of collisions and their interactions as recorded in naturalistic driving experiments. AI and advanced computing techniques are suitable to mine data, find associations and train models easier compared to the past, when data were processed mainly using statistical techniques, which in many cases yielded poor results.

There are several areas of transportation safety and security on which AI techniques are applied, including road safety, AV, maritime safety, rail safety, transportation infrastructure safety, traveller safety, transit safety, freight and commercial vehicle safety and disaster response and evacuation, wide-area alert, and hazardous material (hazmat) safety. The peculiarities of each field's collision risk should be considered, such as that it is associated with different users or it has different characteristics. This paper reviews the ML and AI methods and approaches used in different transportation modes to solve safety problems that so far have been difficult to solve using classical mathematics. Among others, these methods include statistical methods, algorithmic approaches, ANN, and evolutionary computing and are mainly employed to tackle issues related to prediction, clustering and optimization. The presentation of each one of the methods' theory and characteristics is beyond the scope of this paper (the reader can refer to [4] for details); the focus of this paper is the implementation potential of the methods in different transport safety problems. This work was carried out within the RHAPSODY project funded by the European Commission within the Horizon 2020 programme [5].

## 2. Methodology

This literature review focused on the four main transportation modes i.e. road, rail, maritime and aviation and research was divided into those sub-sections. Emphasis was given on the subsection of road, which is the transportation mode with currently emerging AI developments and raises very high research interest among the others. The methodology chosen to perform this review was the systematic literature review because it helps to i) understand the state-of-the-art research in technology-related fields [6], ii) understand existing studies and supports readers in identifying new directions in the research field [7] and iii) it helps to create a foundation for advancing knowledge. The procedure used was based on a similar approach followed by [8] that is comprised from the definition of the research questions, the identification of search string(s), the selection of the sources and search engines, study selection criteria, and data mapping.

[1] * Corresponding author. Tel.: +31-152-784-560;
*E-mail address:* D.Tselentis@tudelft.nl

The two research questions that this study addresses are: 1) Which AI-related techniques are used in the field of transport safety? and 2) Which problems these techniques attempt to address in different transport modes? The search strings were designed based on the synonyms of the main concepts of the investigated topics: artificial intelligence, transportation safety and all 4 transportation modes. Therefore, the final search strings used during the search part of this review were a combination of the strings “safety”, “transportation”, “road”, “rail”, “maritime”, “aviation”, “artificial intelligence”, “machine learning”. Papers selected for presentation and discussion within this research were searched in a large set of scientific peer reviewed Journals and Conferences, filtered for papers published after 1995, and with emphasis on more recent ones, as well as those with quantitative analysis. Papers not contributing in addressing this review’s scope were not taken into consideration, ending up with 50 papers out of the 2,874 initially found.

## 3. Analysis and Results

The results of the review indicate that the main AI techniques that are used in transportation safety belong to the methodological approaches of regression analysis, classification, clustering, mathematical optimization and ANN [3, 9, 10]. More details on the specific methods used are presented in the following sub-sections together with the types of problems addressed.

### 3.1 Road

The data sources that are most commonly used in the BD era of road safety and IoV are smartphones and AV sensors. The intelligent systems and applications related to road safety and crash prediction found in recent research comprise intelligent systems for visual monitoring, accidents modelling and analysis, determining the causes of an accident, driver fatigue detection, dangerous driving identification, automatic incident detection and automated braking systems [11].

Over the past decades, significant research effort has focused on the identification of the time, location and the severity of an incident and comprise several approaches, from manual reports to fully automated procedures using AI techniques including ANN. Of course, manual procedures such as manual reports can cause delays in incident detection, whereas automated procedures can accelerate detection speed by measuring the evolution of the flow characteristics using data collected from on-road sensors [3]. This model used speed, flow and occupancy data, averaged across all lanes. [13] investigated the severity characteristics of abnormal events at intersections by using video processing techniques and statistical deviation analysis methods. This study used a combination of AI methods namely, Hidden Markov Model (HMM), Maximum Likelihood, and k-Nearest Neighbourhood (kNN) and Support Vector Machines (SVM) to classify vehicle abnormalities as speed violation, abnormal fast driving or intentionally wrong turns. A new approach was introduced by [14], who evaluated the performance of several AI methods on incident detection i.e. Multi-Layer Feed Forward Neural Networks (MLFNN), Probabilistic Neural Network (PNN), SVM, and Fuzzy-Wavelet Radial Basis Function NN using data from traffic simulator.

AI can play an important role to predict road crashes and mitigate their severity, by developing crash prediction and pattern identification models that enable policy-makers to forecast crash occurrence and take precautionary measures taken to avoid it. [15] first introduced the spatiotemporal correlation as an important characteristic of traffic accidents and used a long short-term memory (LSTM) model of high accuracy to predict the risk of traffic accidents. The results were tested and evaluated based on a traffic accident database in Beijing, China and illustrated effectiveness and applicability of this method. There are also researchers that combined machine learning approaches such as K-means or K-medoids clustering, expectation maximization (EM) algorithm and a priori algorithm to discover hidden patterns in datasets with historical crashes [16]. [10] also attempted to discover driving behaviour patterns and create groups of drivers using mathematical optimization and AI techniques.

The scientific field of AV and ADAS are probably those that rely the most on AI capabilities among all other road transportation fields. A significant part of AV functionality is the detection of objects, road users and in general, the road environment such as [17] that studied the recognition of the pedestrian movement direction using Convolutional Neural Networks (CNN) and a total of more than 9,000 images from video recording. The models reached a satisfying level of accuracy of 84%. LSTM have also proved to perform well in pedestrian trajectory prediction. Based on this approach, [18] introduced a self-learning system for road user trajectory prediction at intersections with connected sensors, which learns intersection specific pedestrian movement patterns. New advancements are also noticed during the past decades in the developments of ADAS. [19] focused on lane changing prediction by developing an assistance system for mandatory lane changes at drop lanes using a combination of two classifiers, a decision-tree and a Bayes model. A deep learning technique was also employed by [20] for real time detection of lanes and cars in highways. The researchers trained a CNN model, using a dataset of over 630,000 images of vehicle bounding boxes and lanes annotations, collected from a camera, lidar, radar and GPS sensors.

### 3.2 Rail

In Railway systems, safety is a critical aspect of the overall operations. This review identified that AI techniques are mainly applied in the fields of Rail Defect Detection and Rail Obstacle Detection. Of course, this does not mean that AI techniques are not applied in other Railway safety fields like in [21] that employed a decision tree (DT) method in safety classification and the analysis of accidents at railway stations to predict the traits of passengers affected by accidents.

Over the last couple of decades, research has started moving toward the development of computer vision (CV) algorithms for automatically locating and identifying defects on rails. An experimental comparison of 3 different filtering approaches, namely Gabor filter, Wavelet transform and Gabor wavelet transform, was made by [22], based on texture analysis of rail surfaces, to detect the location of rail corrugation on a rail. This research used images captured from a DALSA line scanner with 512 pixels of resolution. SVM and CNN are also tested for wheel defect detection and have shown a relatively good performance [23].

Despite the fact that environment perception and object detection is equally important to trains and autonomous vehicles, research on obstacle detection in railways is not as extensive as in road [12]. According to the same study, vision-based obstacle detection methods can be divided into traditional CV-based and AI-based. Another approach that performs well for obstacle detection is based on background subtraction that is applicable to moving cameras and that uses reference images as baselines [24]. To this end, a comparison between the live on-board camera image of the scene in front of the train and a reference image was made. [25] worked with images collected from the Internet e.g. people, trains, animals and used the residual learning units to train a Fast R-CNN, which achieved an accuracy of 94.85%.

### 3.3 Maritime

Although AI and BD play a very important role in the decision-making of many industries nowadays, the maritime industry is one of the oldest and traditional industries to rely mainly on expertise and experience rather than on data collection and analysis, mostly because of the vast size of network and planning problems [26]. According to the same review, AI techniques are exploited mainly in digital transformation of the maritime industry, applications of big data from automatic identification systems (AIS), energy efficiency and predictive analytics of which, applications of big data from AIS and predictive analytics are related to transportation safety [27]. Nonetheless, relevant AI and BD applications have recently been launched for real-time maritime intelligence [28].

[29] employed CNN models using super resolution satellite data to enhance vessel detection, counting and recognition for maritime surveillance tasks. According to the authors, this methodology can be further extended and specialized into the detection of ghost ships or monitoring of critical infrastructure near harbours or protected areas. With an aim to improve visual recognition, [30] also used a CNN-based framework, focusing on the classification and identification of maritime vessels. This approach was trained based on the MARVEL dataset and showed an improved accuracy.

Several approaches have been followed for incident detection in maritime. [31] used Bayesian networks for anomaly detection in vessel tracking whereas [32] proposed a novel two-step approach where left-to-right HMM are used to represent patterns that are classified using SVM. Suspicious activities are differentiated from unobjectionable behaviour by exploring fusion of data and information, including kinematic features, geospatial features, contextual information and maritime domain knowledge. [33] presented an anomaly/ incident detection approach using SVM as a pattern classification technique. AIS data of 3 months from Port Klang were used and consisted of 9,845 observations, including vessel's Maritime Mobile Service Identity, status, speed, longitude, latitude, course, heading and timestamp. Finally, [34] developed a data-driven non-parametric Bayesian model, based on Gaussian Processes, to model normal shipping behaviour, which was trained using AIS data. The model estimates a measure of normality for each transmission observed depending on its velocity and current coordinates.

### 3.4 Aviation

There exist several areas of use of AI applications in the aviation sector. Those include support for operational decisions by the crew, intelligent crew interface, air traffic data collection/ processing/ analysis for air traffic control systems, optimization of the airspace structure to maximize real aircraft flows, optimization of aircraft routes in the airport area, unmanned aerial systems detection and collision prevention, aviation computer training, diagnostics of airborne components and assemblies, management automation, combat missions solution [35].

It is found that AI can assist the flight journey management more effectively than humans [3]. [36] exploited on-wing data from an engine of a commercial aircraft for engine health assessment. To this end, the authors used the PNN approach that proved to be able to correctly identify the subsystem fault.

[37] developed a genetic algorithm capable of generating trajectories of specified length for the on-board flight path safety system. When the separation standards with other aircrafts are not met by this system's speed control, this algorithm acts to minimize the increase of the trajectory length. An intelligent landing control system of civil aviation aircrafts was developed by [38]. This system manages wind disturbance problems during the landing phase when simultaneously subjected to severe winds and failures e.g. stuck control surfaces. The

architecture of the system includes a dual fuzzy neural network (DFNN) controller, which is capable of implementing fuzzy inference in general and neural network mechanism in particular. An improved performance of the conventional automatic landing system is noticed during simulation tests.

## 4. Conclusions

This research reveals the increasing interest of transportation researchers and practitioners in AI applications to utilize tools and methods developed by the AI community for transport safety purposes. This increase is mainly attributed to the increasing capabilities in data storage and processing, especially due to the recently emerged cloud computing, and is expected to be expanded to all transportation safety sectors in the decades to come. The advancements of AI are expected to greatly benefit transportation safety through applications in all transportation modes including road, railways, maritime and aviation, and particularly the safety issues of autonomous systems within these four domains. Despite the great benefits that AI techniques are expected to bring, there are certainly also several challenges, concerns and obstacles that need to be tackled before fully adopting those techniques into transport safety e.g. the large size of data collection required, the representativeness of data samples collected, the intentional malicious manipulation of training datasets, cyber security and regulation concerns, ethics and social acceptability issues, and the determination of safe and risky boundaries. This research also revealed that there is a lower number of studies on AI applications in maritime and aviation compared to road. This is mainly attributed to the fact that road AI developments are a new and very complex concept whereas the other two have been developed for more decades and are more industrial rather than research concepts. Other urban transportation AI concepts such as air urban transport, last mile delivery drones and public transport were not excluded from this study but did not appear in the search made since research focuses more on the efficiency and acceptability, and less on the safety aspects of those systems.

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