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The usefulness of artificial intelligence for safety assessment of different transport modes

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ABSTRACT

Recent research in transport safety focuses on the processing of large amounts of available data by means of intelligent systems, in order to decrease the number of accidents for transportation users. Several Machine Learning (ML) and Artificial Intelligence (AI) applications have been developed to address safety problems and improve efficiency of transportation systems. However exchange of knowledge between transport modes has been limited. This paper reviews the ML and AI methods used in different transport modes (road, rail, maritime and aviation) to address safety problems, in order to identify good practices and experiences that can be transferable between transport modes. The methods examined include statistical and econometric methods, algorithmic approaches, classification and clustering methods, artificial neural networks (ANN) as well as optimization and dimension reduction techniques. Our research reveals the increasing interest of transportation researchers and practitioners in AI applications for crash prediction, incident/failure detection, pattern identification, driver/operator or route assistance, as well as optimization problems. The most popular and efficient methods used in all transport modes are ANN, SVM, Hidden Markov Models and Bayesian models. The type of the analytical technique is mainly driven by the purpose of the safety analysis performed. Finally, a wider variety of AI and ML methodologies is observed in road transport mode, which also appears to concentrate a higher, and constantly increasing, number of studies compared to the other modes.

1. Introduction

1.1. Background

Artificial Intelligence (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 (Nilsson, 1982). It is the theory and development of computer systems able to perform tasks normally requiring human intelligence, such as reasoning, visual perception, speech recognition, automated learning and scheduling, decision-making and translation between languages. AI leverages computers to mimic the problem-solving and decision-making capabilities of the human mind. Machine Learning (ML) is a branch of AI that develops algorithms imitating human way of learning from data and gradually improving prediction accuracy on the basis of data.

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, also in the transportation domain. This, along with the increase in the information technologies' penetration and use by drivers (e.g. smartphones), the technological advances in sensor devices (e.g. smartphones, autonomous vehicles (AV), vessel telematics, cameras), provide new potential for driver/operator behaviour monitoring, vehicles communication, surveillance and incident detection in all transport modes (road, rail, maritime, aviation). The adoption of these technological advances is widespread because they present many advantages due to high market penetration rates, and IoT and IoV connectivity. This leads to a new era where massive amounts of data are being collected from numerous data sources, stored and managed, which is known as the BD era. A typical example is the number of connected vehicles, which is rapidly increasing every year. It was predicted that by the year of 2020 one fifth vehicles on road will have Internet connection and the global vehicular traffic was expected to reach 300,000 Exabyte (Xu et al., 2017). First results from related applications (Theofilatos et al., 2017; Tselentis et al., 2017) have confirmed the efficiency and usefulness of such BD collection schemes for safety assessment purposes.

One of the biggest challenges in this new era is the management and exploitation of massive data. In order to reveal valuable insights, data

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should be analysed properly. It would seem chaotic to manage and analyse this information if AI was absent. AI enables working expertly with data analytics and this is the primary reason why it is now seemingly inseparable from BD (Kibria et al., 2018). AI and deep learning are capable of pulling from every data input and using those inputs to generate new rules for future analytics. To this end, the “AI machine” is fed by BD in order to turn it into a smart procedure. One of the greatest assets that AI illustrates, regardless of the industry, is its learning ability, its capacity to recognize data trends and its adaptation to changes and fluctuations in those trends. Through making predictions, and identifying patterns and outliers in data, AI can adjust as necessary and provide valuable insights. Although AI is a relatively old concept, the reason it is emerging during the past few decades is the recent advancements in machines computational power and the new capabilities in cloud storage and computing, which make the exploitation of BD using AI techniques feasible. Therefore, through the use of AI techniques like natural language processing, pattern recognition, and machine learning algorithms, on devices, sensors linked with the IoT and IoV, we can now reap immense benefits of BD over numerous fields (Xu et al., 2021).

Transportation systems are complex systems involving a very large number of components and different parties, each having different and often conflicting objectives. With respect to safety problems of different transportation modes (road, rail, maritime and aviation), the focus is on the intelligent systems related to accident prevention and severity mitigation, accident modelling, accident frequency analysis, in-depth investigation of accident causes, accidents evaluation, human factors, dangerous driver/operator behaviour identification, automatic incident detection and monitoring, obstacle detection, with the aim to decrease the number of accidents for transportation users (Machin et al., 2018). To this end, it is important to process all data that can potentially be gathered and extract useful insights. Several Machine Learning (ML) and AI applications have been developed in recent years to address some of the aforementioned problems and improve efficiency and safety of transportation systems. The interest into ML and AI is increasing among transportation researchers and practitioners during the last decades as we are moving into an era of significantly higher computational power that the previous decades (Abduljabbar et al., 2019). AI methods are being used in most transportation safety fields but there is no exchange of knowledge among them yet.

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 (e.g. conflicts and near-misses) and their interactions as recorded e.g. through videos or sensors. AI and advanced computing techniques are particularly suited to mine these data, find associations between them and train models based on these data compared to the past, when data were processed mainly using statistical techniques, which in many cases yielded poor results.

1.2. Objectives

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 (Tselentis et al., 2019; Xue et al., 2019). The particularities of each field’s collision risk should be considered, such as that it is associated with different users (e.g. vehicle driver or airplane pilot) or it has different characteristics (e.g. increased when taking off or landing in aviation and proportional to distance travelled in road safety).

The objective of this research is to address three research questions: 1) Which AI-related techniques used in the field of transport safety are the most promising?, 2) Which problems these techniques attempt to address in different transport modes, and to what extent they are successful? and 3) What is the knowledge and experience that could be shared from one transportation mode to the other? This paper reviews the ML and AI methods and approaches used in different transportation modes to solve safety problems that so far has been difficult to solve using classical mathematics. This work was carried out within the RHAPSODY project funded by the European Commission within the Horizon 2020 programme (“Rhapsody: Recognition of HumAn PatternS of Optimal Driving for safetY of conventional and autonomous vehicles” of the European Union’s Horizon, 2020).

This paper is organised as follows: Section 2 presents the literature review methodology and study selection criteria. Section 3 provides a summary of main AI and ML methods and their main advantages and features. Section 4 includes the results of the literature review per transport mode and analysis purpose. Section 5 presents a discussion of the review results, followed by the conclusions of our study in Section 6.

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 the highest number of casualties and at the same time currently emerging AI developments. This is also evident from the fact that there are numerous researches focusing on scientific fields such as driving behaviour and AV.

The methodology chosen to perform this review was the semi-systematic literature review (Rogers et al., 2020) because it helps to i) understand the state-of-the-art research in technology-related fields (Scornavacca et al., 2006), ii) understand existing studies and supports readers in identifying new directions in the research field (Jones and Gatrell, Jul. 2014) and iii) it helps to create a foundation for advancing knowledge. The procedure used was based on a similar approach followed by (Nascimento et al., 2020) 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.

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 contained at the Science Direct, Scopus and Google Scholar databases, filtered for papers published after 1995, when the concept of ML and AI started to become popular, and with emphasis on more recent ones, as well as those with quantitative analysis. This horizon was selected to capture older concepts such as in aviation and also more recent ones e.g. AVs. Papers not contributing in addressing this review’s scope were not taken into consideration, ending up with 54 papers out of the 2,874 initially found. This was done in 5 steps as follows (Fig. 1):

A) The initial search performed in 2021 using the strings “safety”, “transportation”, “road”, “rail”, “maritime”, “aviation”, “artificial intelligence”, “machine learning” resulted in 2,874 papers.

B) Papers dated before 1995 were filtered out reaching to 2,341 papers.

C) After removing the duplicated records and keeping the potentially relevant articles, the remaining papers were 1,262.

D) Filtering papers based on the title and abstract resulted in 214 papers.

E) Finally, after reading the full papers, the final total number of relevant papers found was 54.

It is clarified at this point that it was necessary to filter papers based on title, abstract and full paper since several papers were returned by the search engine, which included words such as safety and artificial intelligence in their title or main text but they were found not to be related to

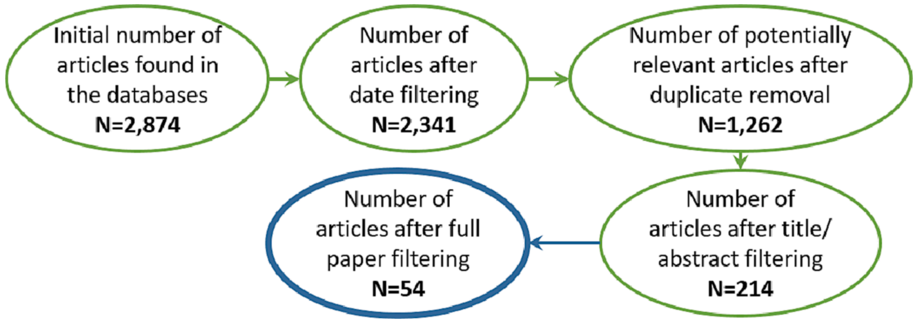

Fig. 1. Search strategy followed by this literature review.

this topic. Examples of these topics that were not 100% relevant were referring to i) process, control, operation or navigation of a vehicle, train, vessel or aircraft, ii) security in high transportation areas, iii) other safety and security issues that are indirectly affecting transportation safety e.g. cyber-security and malware, and iv) transportation safety in a different transportation mode than those 4 examined herein.

3. Overview of AI and ML methods

This section provides a short overview of the AI and ML methods' theory and characteristics; the reader may refer to (Bonaccorso, 2017) for further details. Artificial Intelligence and Machine Learning methodologies can be grouped into supervised and unsupervised learning methods. Supervised learning methods, such as classification and regression, are based on historical data and make use of labelled datasets (e.g. gender) in order to train algorithms that can accurately classify data or predict outcomes. On the other hand, unsupervised learning methods, such as clustering and dimension reduction, are not based on prior knowledge to analyse data with the scope to cluster unlabelled datasets, create association rules and reduce data dimensionality.

Regression, which is the most commonly used regression methodology, is a statistical, supervised learning method that determines the strength and character of the relationship between i) one dependent variable (Y variable) and ii) one or more independent variables (X variable(s)). The final outcome of a regression model is the prediction of a numerical value based on previously observed data. In transport safety sciences, regression models are used to analyse the relationship between collisions and several characteristics such as the traffic volume, the environment, the geometry of the infrastructure and users' demographics (Washington et al., 2020).

Classification is also a supervised learning method that categorizes a set of data into two (binary) or more classes (multi-class) based on historical labelled data, when there is a prior knowledge on the class of the observations. Classification methods are mainly represented by methods such as Artificial Neural Networks, Support Vector Machines (SVM), logistic regression, decision trees and k-nearest neighbours. Typical examples of transport safety problems that can be formulated as classification problems are driver manoeuver classification, choice models, pedestrian detection and traffic light detection. Regarding SVM, it is a computer algorithm that learn by example (supervised learning) to assign labels to observations (Noble, 2006). This is achieved by creating support vectors that are data points closer to the hyperplane, which are used to maximize the margin of the classifier. These points help build the SVM and their deletion would result to a change in the position of the hyperplane.

Regarding unsupervised learning methods, clustering is probably the most favourite methodological family. It refers to the organization of unlabelled data into similar groups called clusters using metrics that identify their common attributes. This ends up to the collection of data items which are "similar" between them, and "dissimilar" to data items in other clusters. To this end, some proximity measures are calculated, which are used as criterion functions to assess similarities. Examples of clustering algorithms are K-means, hierarchical and DBSCAN, which are used in studies such as driver/user profiling, driving pattern recognition or crashes pattern detection.

Methodologies related to dimensionality reduction are also part of the unsupervised learning family. The difference compared to clustering techniques is that dimensionality reduction such as Principal Component Analysis (PCA) aims to group and reduce the number of input variables and not to group the observations of a dataset as clustering techniques do. This is particularly useful in cases when a dataset has numerous variables that can be grouped into fewer components or constructs with homogeneous variables.

Apart from the supervised and unsupervised methodologies, there is also optimization that is a standalone AI methodological family that is used in processes where finding an optimal solution is the goal. These optimization problems have the goal to either maximize or minimize an objective function, e.g. transportation safety risk, using some or no constraints. Depending on the case, they can be linear, non-linear or mixed integer optimization problems and they may be targeting at an exact or a heuristic/approximate solution. An example of heuristic search algorithms are the genetic algorithms, which have been used in safe driving optimization of autonomous vehicles, automated evolutionary design of driving agents and autonomous smart vehicle parking systems. In short, the genetic algorithm approach is based on the concept that the "strongest" (or "fittest") are the ones to survive. These algorithms belong to the evolutionary algorithms since they emulate the evolution process, where the strongest elements become stronger and remain active while the weakest elements are eliminated (Sivanandam and Deepa, 2008).

It is highlighted that ANNs can be employed for both supervised (regression/ prediction and classification) and unsupervised (clustering) learning tasks. The output of an ANN depends on its type and structure. A part of the ANN algorithms that imitate the brain's structure and function is Deep Learning. It allows computational models that are composed of multiple processing layers to learn representations of data with multiple levels of abstraction. Deep learning discovers intricate structure in large data sets by using the backpropagation algorithm to indicate how a machine should change its internal parameters that are used to compute the representation in each layer from the representation in the previous layer (LeCun et al., 2015). The higher the number of hidden layers of an ANN, the deeper the network is considered.

Many algorithms reviewed herein are based on fuzzy logic. According to (Kosko and Isaka, 1993), fuzzy logic is a branch of machine intelligence that helps computers paint grey, common-sense pictures of an uncertain world. When mathematicians lack specific algorithms that dictate how a system should respond to inputs, fuzzy logic can control or describe the system by using common-sense rules that refer to indefinite quantities. In other words, fuzzy logic is a form of logic, where the truth value of variables may be any real number between 0 and 1 and not either 0 or 1. When the truth value may range between completely true and completely false, fuzzy logic is employed to handle the concept of partial truth.

4. Analysis and results

This section will present the results of the review per transport mode and application area. More details on the specific methods used are presented in the following sub-sections together with the types of problems addressed.

4.1. Road

Road safety and accident prediction constitute a significant part of the Intelligent Transportation Systems that aim to prevent or mitigate the severity of traffic crashes, thereby increasing the chances of drivers and passengers' survival, as well as to analyse and process the circumstances under which crashes occur (Machin et al., 2018). Factors causing road crashes include human factors e.g. driving behaviour, environmental or traffic conditions and road state. To prevent those, it is crucial to be able to process all data gathered by in-vehicle sensors and extract valuable insights in a proactive way to handle situations where safety is compromised. The data sources that are most commonly used in the BD era of road safety and IoV are smartphones and sensors installed in AVs, connected vehicles and ADAS systems. The intelligent systems and applications related to road safety and crash prediction found in recent research comprise 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 (Machin et al., 2018).

4.1.1. Incident detection

Over the past decades, significant research effort has been made to develop incident detection mechanisms able to automatically detect the occurrence of an incident, e.g. accident or traffic incident, on several road types. These efforts focus 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 reports can cause delays in incident detection, whereas automated procedures can accelerate detection speed by measuring the evolution of the traffic flow characteristics using data collected from on-road sensors (Abduljabbar et al., 2019). Initially, algorithms used for incident detection were based on statistical techniques such as California Algorithm but eventually this approach was deemed difficult to be applied on arterial roads, due to the street parking and traffic signals. To this end, AI-related approaches such as ANN are commonly used in literature. For instance, (Dia and Rose, 1997) developed a multi-layer feedforward (MLF) neural networks (NN) to detect incident occurrence in a freeway, using field data from 100 incidents. This model used speed, flow and occupancy data, averaged across all lanes. A real-time vehicle detector was developed by (Stojmenovic, 2006) using a novel variant of the Adaptive Boosting (AdaBoost) learning algorithm with the fastest training time and with competitive detection and false positive rates. (Aköz and Karsligil, 2011) 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 (Ghosh and Smith, 2014), who evaluated the performance of several AI methods on incident detection i.e. AI methods: Multi-Layer Feed Forward Neural Networks (MLFNN), Probabilistic Neural Network (PNN), SVM, and Fuzzy-Wavelet Radial Basis Function NN using data from traffic simulator. Finally, an innovative data collection method through Twitter showed that it is a feasible and cost-effective solution that can potentially address the incident identification problem (Gu et al., 2016). The authors applied the semi-naïve Bayes classification model to classify tweets as either traffic incident or non-traffic incident by processing and filtering incident data coming from tweets.

4.1.2. Crash prediction and pattern identification

AI can play an important role to predict road crashes and mitigate their severity, by developing crash prediction and pattern identification models capable of capturing spatiotemporal changes of crashes and identify their patterns. (Ren et al., 2018) first introduced the spatio-temporal 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. Other studies have also exploited deep learning structures such as in (Rezaie Moghaddam et al., 2011) where ANN were used together with road data related to traffic and geometrical characteristics from the capital of Iran to model and estimate crash severity and to identify significant crash-related factors in urban highways. There are also other examples of NN applications to predict intersection crashes, e.g. in Macomb County of the State of Michigan, USA (Darccedil and Buuml, 2010). The model developed, aiming to model the non-linear relationship between the crash types and crash properties such as time, weather, light and surface conditions, driver and vehicle characteristics, showed high capability of providing a very accurate prediction (90.9%) of the crash types.

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 (Vasavi, 2018). (Ali and Bakheit, 2011) tested the accuracy of different AI approaches and more specifically, ANN, multiple regression and principal component analysis to predict the future trend of annual vehicle crash casualties. Finally, (Wahab et al., 2009) implemented and benchmarked statistical, ANN, and fuzzy NN techniques in order to reveal driving patterns that may lead to accurate driver profiling models. Models were trained using driving data collected from in-car signal corpus. (Papadimitriou et al., 2019; Tselentis et al., 2019) also attempted to discover driving behaviour patterns and create groups of drivers using mathematical optimization and AI techniques.

4.1.3. AV and advanced driver-assistance systems (ADAS)

The scientific field of AV and ADAS are probably those that rely the most on AI capabilities among all other road transportation fields. It is necessary for their functionality to use approaches that enable vehicles to understand the road environment and geometry, identify their surroundings, navigate to their destination and teach themselves how to drive safely e.g. respect speed limits and highway code rules, maintain safe headways, lane discipline and control.

The main topics of the relevant AV studies so far include sensors and perception, navigation and control, fault prevention, conceptual model and framework, human factor, fault forecasting, ethics and policies, and dependability and trust (Nascimento et al., 2020). Among others, the most commonly used AI methods in AV research are ANN, SVM, Fuzzy Logic, Bayesian Artificial Intelligence, Hidden Markov Based Models, Nearest-Neighbours-Based Algorithm, Adaptive Boosting, Optimization Heuristics, Regression-Based Models and Principal Components Analysis (PCA) (Nascimento et al., 2020).

It was also aforementioned that a significant part of AV functionality is the detection of objects, road users and in general, the road environment. For instance, (Dominguez-Sanchez et al., 2017) 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, (Bock et al., 2017) introduced a self-learning system for road user trajectory prediction at intersections with connected sensors, which learns intersection specific pedestrian movement patterns. A vision recognition system was developed by (Jeon et al., 2016) that was based on an algorithm capable of detecting various objects, namely pedestrian, traffic sign and traffic light. This research used a single monocular camera for autonomous vehicle in real driving conditions. A combination of AI methodologies was used including Histogram of Gradients (HOG) features, PCA, SVM for pedestrian detection, canny edge detection for traffic lights and a NN-based classifier.

New advancements are also noticed during the past decades in the developments of ADAS. ADAS are advanced driver-assistance systems such as Adaptive Cruise Control, Adaptive Light Control, Automatic Parking, Traffic sign recognition, Navigation System, Night Vision, Blind Spot Monitoring, Automatic Emergency Braking, Driver Drowsiness Detection and Driver Monitoring System that are relying majorly on AI and ML in order to function. One of the most commonly developed models in ADAS are the lane changing models. (Hou et al., 2013) 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. (Morris et al., 2011) also developed a lane changing classifier to predict a driver's intention to change lane based on a novel approach using Relevance Vector Machine (RVM), a Bayesian extension to SVM. A model based on a Multi-Layer Perceptron Neural Network (MLPNN) was proposed by (Lee and Yeo, 2016) to develop a system for real-time Collision Warning. The factors taken into account were the distance between preceding and following vehicle, the speed and acceleration of the following vehicle, and the speed and deceleration of the preceding vehicle. A deep learning technique was also employed by (Huval et al., 2015) 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. Finally, it is also essential in ADAS to predict the remaining useful life of a system, which is a task that is also based on AI developments. For instance in (Taie et al., 2016) where a remote diagnosis, maintenance and prognosis (RDMP) framework for ADAS was presented using kNN, SVM regression and NN.

4.2. 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 (Alawad et al., 2019) 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.

4.2.1. Rail defect detection

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 (Mandriota et al., 2004), 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 high resolution. (Hajizadeh et al., 2016) tackled the drawback of the highly imbalanced sample towards the non-defective class and the fact that there is a large number of unlabelled data samples by deploying a semi-supervised rail defect detection model. Data were recorded through a high resolution camera covering 700 km of rail. A two-steps algorithm for rail defect detection that combines traditional object localization and CNN was proposed by (Shang et al., 2018). 5,793 cropped training images that focus only on the rail part are initially received through the integration of traditional image processing methods. Thereafter, cropped images are parsed into a CNN to extract part-level features for rail images classification. SVM and CNN are also tested for wheel defect detection and have shown a relatively good performance (Krummenacher et al., 2017).

4.2.2. Rail obstacle detection

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 (Ristić-Durrant et al., 2021). According to the same study, vision-based obstacle detection methods can be divided into traditional Computer Vision (CV)-based and AI-based. In some researches (Ukai, 2004), different detection methods are applied for moving and stationary objects on the track. Moving obstacle detection is performed using an optical flow method within the Region of Interest (ROI), while the Sobel edge detection method followed by morphological processing of the edge detected image is used for the detection of the stationary objects. 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 (Mukojima et al., 2016). 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. Regarding AI-based methods, (Manikandan et al., 2017) developed an early warning system using vision based, artificial intelligence and sensors. The first methodology proposed in this research was the ADA boost algorithm applied on data collected from a single thermal camera to detect obstacles in level crossings and to calculate the distance between detected obstacles and the train. The second was based on image processing and an artificial intelligence camera setup to identify the landslides over the rail track. (Yu et al., 2018) worked with images collected from the Internet e.g. people, trains, animals to train a Fast Region-based CNN (Fast R-CNN that is a CNN variant), which achieved an accuracy of 94.85%. This network used the residual learning network block to optimize the network structure. Finally, (Pamuła and Pamuła, 2021) developed a model for detection of obstacles at rail level crossings based on video from monitoring cameras, using a CNN to determine the state of ROI area that is vital for the safe passage of the train.

4.3. 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 (Munim et al., 2020). 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, out of which, applications of big data from AIS and predictive analytics are related to transportation safety (Xue et al., 2019). Nonetheless, relevant AI and BD applications have recently been launched for real-time maritime intelligence (https://www.marinetraffic.com/).

4.3.1. Maritime Surveillance

(Fontana et al., 2020) 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 ships not tracked by the radars or monitoring of critical infrastructure near harbours or protected areas. With an aim to improve visual recognition, (Solmaz et al., 2018) 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. Finally, the review of (Soldi et al., 2021) on the use of AI techniques for global maritime surveillance showed that new opportunities are emerging for target detection, segmentation, and classification due to the availability of multiple space-based sensors using advanced image analysis approaches. The authors showed how synthetic aperture radar (SAR), high resolution and very high resolution images is exploited in literature with the use of deep learning and machine learning approaches.

4.3.2. Incident detection

Several approaches have been followed for incident detection in maritime. (Handayani and Sediono, 2015) used Bayesian networks for anomaly detection in vessel tracking whereas (Shahir et al., 2015) proposed a novel two-step approach where 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. (Handayani et al., 2013) 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.

(Rhodes et al., 2007) tested an improved neuro-biologically inspired algorithm for situation awareness in the maritime domain. The algorithm receives tracking information and learns motion patterns in real-time, which enables models' well adaptation to evolving situations and maintains high performance levels at the same time. Models that are constantly refined by the concurrent incremental learning, are used for vessel behavioural pattern evaluation based on motion states. The advantages of Bayesian Networks (BN) to i) easily include expert knowledge into the model, and ii) facilitate the understanding and interpretation of the learned model for humans, has established this method as a good performing solution for detection of anomalous vessel behaviour (Johansson and Falkman, 2007). In this research, a BN approach was tested on synthetic data and their results indicated a good performance of the model in detecting the single-object anomalies such as speeding. (Lane et al., 2010) focused on the identification of five anomalous ship behaviours that can be monitored using AIS transmissions. The goal was to develop a process for each behaviour that determines the probability that the specific behaviour is anomalous. The five anomalous behaviours investigated were deviation from standard routes, unexpected AIS activity, unexpected port arrival, close approach, and zone entry. Finally, (Kowalska and Peel, 2012) 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.

4.4. Aviation

AI and automation have been part of the aviation sector for many decades, where several AI applications exist. This part of the study will review some recent novel applications. Those include two main groups of applications that are incident diagnosis e.g. unmanned aerial systems detection and collision prevention, aviation computer training, diagnostics of airborne components and assemblies, management automation, combat missions solution, and flight assistance e.g. 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 (Kulida and Lebedev, 2020).

4.4.1. Incident diagnosis

It is found that AI can assist the flight journey management more effectively than humans (Abduljabbar et al., 2019). (Budalakoti et al., 2008) employed an unsupervised machine learning algorithm to cluster landing phase-sequences using the normalized length of the longest common subsequence as a similarity measure. A detailed outlier analysis was applied on approximately 2,200 flight sequences to detect anomalies and results were compared to those of HMM. It was shown that this approach may increase safety when an airplane is landing. Moreover, (Aretakis et al., 2015) 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.

Other research (Williams, 2014) addresses the problem of real-time turbulence forecasting using a methodology that fuses data from diverse data sources including Doppler radar, geostationary satellites, a lightning detection network and a numerical weather prediction model. The model developed for aviation turbulence detection is based on an unsupervised method for classification named Random Forest. This approach enables the avoidance of pre-determined route deviation, fuel minimization and air-control management enhancement.

4.4.2. Flight assistance

(Kulida and Lebedev, 2017) 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 (Xu et al., 2011). 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. An ANN-based PID (proportional integral derivative) controller is developed by (Kumar et al., 2013) to suppress the peak overshoot against disturbances at the airframe dynamics, which severely degrades the response of the system. Results indicated a superiority of the artificial neuro PID controller over the conventional offline PID controller for controlling the pitch attitude of longitudinal autopilot for general aviation aircraft.

5. Discussion

An overview of the papers reviewed in each transport safety field is provided in Table 1. This table demonstrates which transport mode used each specific AI and ML methodology and the purpose for which these techniques were applied. It also shows the type of AI or ML technique, supervised, unsupervised or optimization, that each study applied. Based on this view, someone may draw conclusions on the key findings such as which are the most popular methodologies used across transport modes or which analytical technique to use based on the purpose of the analysis.

5.1. Main findings

5.1.1. Most promising AI techniques used in transport safety fields

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. It was shown that apart from the incident detection field of the maritime transport mode, all other transport safety fields reviewed in this study make use of ANN-related methods. This is probably attributed to the relatively high modelling performance of these methods, especially when employed for image processing, which on the other hand require large data samples for training. SVM, HMM and Bayesian models are also used in most transport modes and mainly for incident detection purposes. Despite the fact that the most popular method for incident detection among those three appears to be Bayesian models followed by SVM and HMM, the latter is used in more transport modes compared to the other two.

The method selection is based on the type of the problem and, the availability and volume of the data. In road transport, a wider variety of methodologies is observed but this may be because of the current interest for new AI applications for road compared to the others. Decision trees classification is also used in railways, while kNN and PCA were exploited in the other two fields of the road transport mode examined i.e. crash prediction, AV and ADAS. Finally, approaches based on K-means, regression, expectation maximization, a-priori, maximum likelihood and wavelet transform were used less frequently and mainly in road transportation. Therefore, another lesson learned is that when incident detection is the scope of a certain safety field, this problem may be formulated as a classification problem and use algorithms such as SVM, HMM and Bayesian models.

5.1.2. Problems solved through AI techniques in different transport modes

It was revealed through this literature review that the different safety problems addressed by these AI techniques in each transportation mode are:

A) Incident detection, crash prediction and AV and ADAS in road transportation.

B) Defect and obstacle detection in rail transportation.

C) Maritime surveillance and incident detection in maritime.

D) Flight assistance and incident diagnosis in aviation.

In most cases, the models developed to address these problems presented high performance and accuracy and showed capability to resolve them despite their high complexity.

5.1.3. Knowledge and experience that could be shared among transportation modes

As mentioned above, there are several studies exploiting ANNs due to their relatively high modelling performance when it comes to image processing, which on the other hand require large data samples for training. This information, i.e. that studies using image data should exploit ANN-based methods, could be exploited across the different

Table 1
Overview of papers per transport safety field that used each AI and ML methodology.

Paper	Transport mode				Purpose of analysis								Type of AI and ML technique																
													Supervised Learning												Unsupervised Learning				Optimization
													Classification										Regression		Clustering			Dimension reduction	
	Road	Railway	Maritime	Aviation	Literature review	Incident Detection	Crash Prediction	AV and ADAS	Defect Detection	Obstacle Detection	Surveillance	Route Assistance	ANN	SVM	Bayesian	HMM	kNN	Decision tree	AdaBoost	Maximum likelihood	Wavelet transform	Fuzzy logic	ANN	Multiple regression	K-means	a-priori	Dynamic time warping	PCA	Optimization
Abduljabbar et al., 2019	√				√																								
Papadimitriou et al., 2019	√										√	√												√					
Tselentis et al., 2019	√						√				√	√																	√
Machin et al., 2018	√				√																								
Dia & Rose, 1997	√					√							√																
Stojmenovic, 2006	√					√													√										
Aköz & Karsligil, 2011	√					√								√		√	√			√									
Ghosh & Smith, 2014	√					√							√	√															
Gu et al., 2016	√					√									√														
Ren et al., 2018	√						√						√																
Moghaddam et al., 2011	√						√						√																
Darccedil & Buuml, 2010	√						√						√																
Vasavi, 2018	√						√																		√	√			
Ali & Bakheit, 2011	√						√						√										√	√				√	
Wahab et al., 2009	√						√						√																
Nascimento et al., 2019	√				√																								
Dominguez-Sanchez et al., 2017	√							√					√																
Bock et al., 2017	√							√					√																
Jeon et al., 2016	√							√					√	√														√	
Hou et al., 2013	√							√							√			√											
Morris et al., 2011	√							√						√	√														
Lee & Yeo, 2016	√							√					√																
Huval et al., 2015	√							√					√																
Taie et al., 2016	√							√					√	√			√												
Alawad et al., 2019		√																√											
Mandriota et al., 2004		√							√												√								
Hajizadeh et al., 2016		√							√					√			√												
Shang et al., 2018		√							√				√																
Krummenacher et al., 2017		√							√				√	√															
Ristić-Durrant et al., 2021		√			√					√																			
Ukai et al., 2004		√								√			√																
Mukojima et al., 2016		√								√																	√		
Manikandan et al., 2017		√								√			√						√										
Yu et al., 2018		√								√			√																
Pamula & Pamula, 2021		√								√			√																
Munim et al., 2020			√		√						√																		
Xue et al., 2019			√																			√							
Fontana et al., 2020			√								√		√																
Solmaz et al., 2018			√								√		√																
Soldi et al., 2021			√								√		√																

(*continued on next page*)

Table 1 (*continued*)

Paper	Transport mode				Purpose of analysis								Type of AI and ML technique																
													Supervised Learning												Unsupervised Learning				Optimization
													Classification										Regression		Clustering			Dimension reduction	
	Road	Railway	Maritime	Aviation	Literature review	Incident Detection	Crash Prediction	AV and ADAS	Defect Detection	Obstacle Detection	Surveillance	Route Assistance	ANN	SVM	Bayesian	HMM	kNN	Decision tree	AdaBoost	Maximum likelihood	Wavelet transform	Fuzzy logic	ANN	Multiple regression	K-means	a-priori	Dynamic time warping	PCA	Optimization
Handayani & Sediono, 2015			√			√									√														
Shahir et al., 2015			√			√								√		√													
Handayani et al., 2013			√			√								√															
Rhodes et al., 2007			√			√							√																
ohansson & Falkman, 2007			√			√									√														
Lane et al., 2010			√			√									√														
Kowalska & Peel, 2012			√			√									√														
Kulida & Lebedev, 2020				√	√																								
Budalakoti et al., 2008				√		√										√													
Aretakis et al., 2015				√		√							√																
Williams, 2014				√		√												√											
Kulida & Lebedev, 2017				√								√																	√
Xu et al., 2011				√								√	√																
Kumar et al., 2013				√								√	√																

transport safety fields. This research also revealed that there is a lower number of studies on AI applications in maritime and aviation compared to road. This was 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. Moreover, apart from the incident detection and diagnosis all other fields are strongly related to each transportation mode such as autonomous flight assistance to aviation and maritime surveillance to maritime. The only safety field from which knowledge and experience could potentially be transferred to the rest of the modes is autonomous vehicles. Knowledge related to the understanding of the surrounding environment, objects, geometry and navigation could be exploited to other fields, e.g. maritime or aviation, as well to improve safety.

5.2. Main challenges and future opportunities

Apart from the expected benefits that AI will bring to society, there are several challenges, concerns and obstacles that need to be tackled before fully deploying these techniques into transport safety. Examples of these challenges (Abduljabbar et al., 2019) include:

- the large size of data collection required and how these could be handled
- the representativeness of data samples collected and what is the correct procedures that should be followed to ensure that
- the intentional malicious manipulation of training datasets and how those could be detected and blocked
- cyber security and regulation concerns and how policy-makers could be supported in this
- ethics and social acceptability issues and how these could be addressed in such a way that society will embrace these changes
- the determination of safe and risky boundaries

In terms of the type of the analytical technique, it appears that it is mainly driven by the purpose of the safety analysis performed. For instance, for incident detection purposes in road, maritime and aviation, only classification models are utilized, which are able to capture the differences between classes or states such as free flow or congested road conditions. Regarding the rail, it also appears that classification techniques are the only ones exploited for defect and obstacle detection, which are mainly based on image classification. Dimension reduction techniques are found to be used only in the road mode, which demonstrates high data dimensionality most probably due to the massive data that are collected in this mode compared to the other three modes examined. On the other hand, models from several types of techniques are used for crash prediction purposes. This reveals that a researcher can approach this field from a different perspective, for instance as a regression problem to predict the exact number of crashes or as a classification problem to predict the crash type. This provides an opportunity that could be exploited in other research fields and transportation modes as well. Other emerging transportation concepts, e.g. air urban transport, last mile delivery drones and Hyperloop, that make significant use of AI and the safety aspects of those systems should also be investigated in the future.

6. Conclusions

Our research revealed 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 enables them to address real transportation problems that were previously challenging to solve based on the traditional solution methods. The AI advancements are greatly benefiting transportation safety through applications in all modes including road, railways, maritime and aviation, and particularly the safety issues of autonomous systems within these four domains. Our results highlighted that a transfer of knowledge among different safety fields is possible and there could be benefits from more systematic mapping of the experiences in the transport safety domain.

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 deploying 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 (Abduljabbar et al., 2019).

The adoption of AVs and ADAS in the future is expected to bring considerable benefits to society, such as traffic optimization and crash reduction. Their heavy dependency on sensor technologies and communication across connected vehicles, the availability of sensors and the ability for fast computing in recent years is gradually raising the interest for AV and ADAS research and have created a vision for an automated and safer transportation system. There are still challenges to overcome though, such as the fast management and processing of huge data amounts that need to be collected, the security and integrity of AV software systems, insurance liability etc., before shifting to a fully autonomous future.

This research has certain limitations. First of all, not all transport modes were reviewed. 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. Nonetheless, these are emerging transportation concepts based on AI and should be examined in the coming years, including the Hyperloop that was not considered in this study and for which the safety aspects has been investigated only on a theoretical level (Mateu et al., 2021). Moreover, future reviews should focus also on other categories of the 4 transport modes investigated, apart from those examined herein. Another limitation of this review is the time period of publications, which was set for studies published within the 1995 to 2021. This should be extended in the future to studies published either before 1995 or after 2021 and repeat this review. Finally, another limitation of this study is that the most significant part of the aviation research is not present in the academic literature mainly due to the fact that it is part of the industrial research and development and most of the times it remains confidential.

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.

Data availability

No data was used for the research described in the article.

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