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THE PLACE AND ROLE OF AI IN TRANSPORT SYSTEMS MANAGEMENT

Ivan Manchev, Dimitar Dimitrov
Todor Kableshkov University of Transport, Sofia, Bulgaria

Abstract. Recent advances in artificial intelligence (AI) have created many machine learning (ML) and AI applications for safer and more efficient transportation. Yet, knowledge exchange between transport modes remains limited. In traffic management, where security is crucial, challenges arise in protecting information and exchanging data between vehicles and infrastructure. Analytical methods in this area include statistical and econometric techniques, algorithmic approaches, classification, clustering, artificial neural networks (ANN), optimization, and dimension reduction. Interest is growing among transport researchers and practitioners in applying AI to crash prediction, incident detection, pattern identification, driver or operator assistance, and route optimization. The choice of analytical techniques depends on the specific safety analysis goals. This article reviews ML and AI methods used across road, rail, maritime, and aviation modes, focusing on their roles in system management and unique safety and security challenge.

Keywords: artificial intelligence (AI); machine learning (ML); transportation safety; internet of things (IoT); safety management; data-driven decision making

1. Introduction

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. 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 the human way of learning from data and gradually improving prediction accuracy based on data. Over the past decades, 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 behavior monitoring, vehicles communication, surveillance and incident detection in all transport modes (road, rail, maritime, aviation) [6].

Advanced transportation systems (ATS) represent a significant evolution from traditional transportation modes by integrating cutting-edge technologies, innovative infrastructure, and progressive policy measures. These systems aim to improve the efficiency, safety, sustainability, and accessibility of transportation networks, addressing the increasing demands of urbanization and environmental sustainability. With growing environmental concerns and technological advancements, electrification has emerged as a pivotal element in this evolution.

Artificial intelligence (AI) has emerged as a key driver in the evolution of ATS. Machine learning (ML), a branch of artificial intelligence, involves creating algorithms that enable computers to learn from data and make predictions based on it. ML offers advanced solutions that can overcome limitations of traditional techniques, providing dynamic, data-driven, and adaptive approaches. ML-based methods have significantly improved predictive maintenance and energy management in ATS by providing real-time monitoring, predictive analytics, dynamic optimization, and improved efficiency [14, 15].

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, traveler safety, transit safety, freight and commercial vehicle safety and disaster response and evacuation, wide-area alert, and hazardous material (hazmat) safety. 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). Reviewed 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 [1, 2, 3].

2. Technological consideration of problem types

More details on the specific methods used are presented in the following sub-sections, together with the types of problems addressed.

2.1. 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 analyze and process the circumstances under which crashes occur. 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, accident modelling and analysis, determining the causes of an accident, driver fatigue detection, dangerous driving identification, automatic incident detection, and automated braking systems [4, 10, 13].

2.1.1. AV and advanced driver-assistance systems (ADAS) The scientific field of AV and ADAS is probably those that rely the most on AI capabilities among all other road transportation fields. Their functionality must 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. 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 has also proved to perform well in pedestrian trajectory prediction. Based on this approach introduced a self-learning system for road user trajectory prediction at intersections with connected sensors was introduced, which learns intersection-specific pedestrian movement patterns [5, 7, 10].

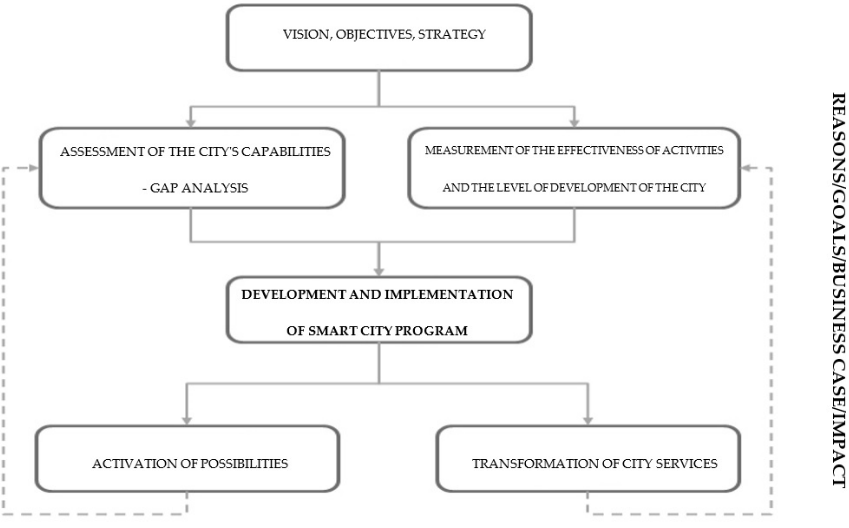

Figure 1. Roadmap for the implementation of a smart city

2.2. 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 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 [13, 17].

2.2.1. 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 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. tackled the drawback of the highly imbalanced sample towards the non-defective class and the fact that there is a large number of unlabeled 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-step algorithm for rail defect detection that combines traditional object localization and CNN was proposed. 5,793 cropped training images that focus only on the rail part were initially received through the integration of traditional image processing methods [18].

2.2.2. 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. 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, which applies to moving cameras and uses reference images as baselines. 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 developed an early warning system was developed using vision-based, artificial intelligence, and sensors. The first methodology proposed in this research was the ADA boost algorithm applied to 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, working 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 developed a model for the 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 [2, 19].

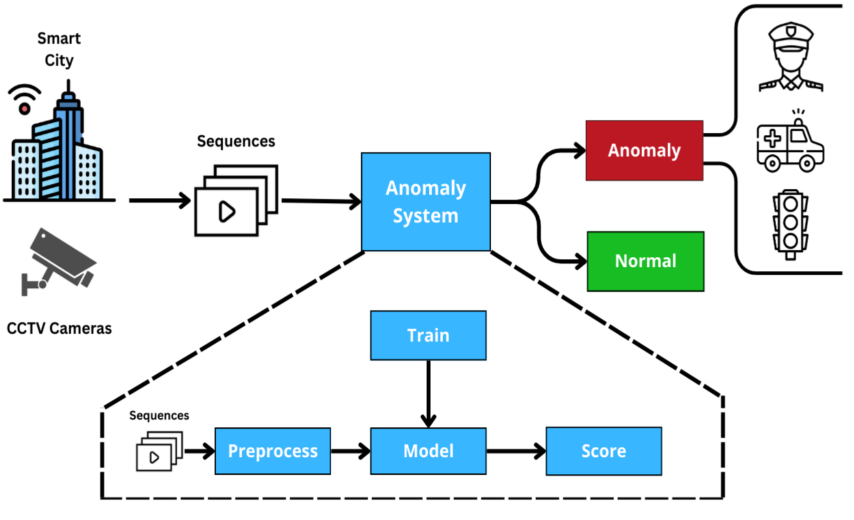

Figure 2. Common architecture of anomaly detection systems in traffic surveillance and its possible integration into a smart city framework

2.3. 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 the network and planning problems. According to the same review, AI techniques are exploited mainly in the 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. Nonetheless, relevant AI and BD applications have recently been launched for real-time maritime intelligence [7, 12].

2.3.1. Several approaches have been followed for incident detection in maritime. used Bayesian networks for anomaly detection in vessel tracking, whereas they proposed a novel two-step approach where HMMs are used to represent patterns that are classified using SVM. Suspicious activities are differentiated from unobjectionable behavior by exploring the fusion of data and information, including kinematic features, geospatial features, contextual information, and maritime domain knowledge. Maritime Mobile Service Identity, status, speed, longitude, latitude, course, heading and timestamp. tested an improved neurobiologically 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 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 the detection of anomalous vessels [8, 9, 10].

2.3.2. Maritime Surveillance employed CNN models using super-resolution satellite data to enhance vessel detection, counting, and recognition for maritime surveillance tasks. 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 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 improved accuracy. Finally, the review of on the use of AI techniques for global maritime surveillance showed that new opportunities are emerging for target detection, segmentation, and classification [11].

2.4. AI and automation have been part of the aviation sector for many decades, where several AI applications exist. 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.

2.4.1. It is found that AI can assist the flight journey management more effectively than humans 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 the results were compared to those of HMM. It was shown that this approach may increase safety when an airplane is landing. Moreover, exploiting on-wing data from an engine of a commercial aircraft for engine health assessment. To this end, the authors used the PNN approach, which proved to be able to correctly identify the subsystem fault. Other research 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 [15, 16].

2.4.2. Developed a genetic algorithm capable of generating trajectories of specified length for the onboard flight path safety system. When the separation standards with other aircraft 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 aircraft was developed by. 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 mechanisms 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 to suppress the peak overshoot against disturbances in 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 the longitudinal autopilot for general aviation aircraft [17].

Conclusion

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 transportation modes. 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. 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 The adoption of AVs and ADAS in the future is expected to bring considerable benefits to society, such as traffic optimization and crash reduction.

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, including the Hyperloop, which was not considered in this study and for which the safety aspects have been investigated only on a theoretical level.

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✉ **Ivan Manchev, MSc.**
ORCID iD: 0009-0006-9513-159X
Department of Technology Organization and Management of Transport
Todor Kableshkov University of Transport
158, Geo Milev St.
1574 Sofia, Bulgaria
E-mail: imanchev@vtu.bg

✉ **Prof. Dimiitar Dimitrov, DSc.**
ORCID iD: 0009-0006-1854-9052
Department of Technology Organization and Management of Transport
Todor Kableshkov University of Transport
158, Geo Milev St.
1574 Sofia, Bulgaria
E-mail: ddimitrov@vtu.bg