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Artificial Intelligence in Transportation

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Abstract: *This introductory article serves as the section's introduction and provides a comprehensive overview of the most recent AI innovations in the transportation sector, with a special emphasis on the advancements that enable automated Mobility-as aService (MaaS). It covers the most recent developments in Intelligent Transport Systems (ITS), including improvements at the vehicle, infrastructure, and management levels, as well as future AI*

Keywords: *Intelligent transport systems (ITS), mobility-as-a-service (MaaS), advanced driver assistance systems (ADAS).*

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I. INTRODUCTION AND BACKGROUND

The transportation sector is essential to maintaining our everyday life.The transportation sector has led the way in digitising its operations by implementing comprehensive data systems and automated agents, covering from the vehicle up to the traffic system, in line with the prior trends of the last 10 years. To understand and control this data, it became mandatory to optimise processes on the micro- and macroscopic level in this complex, everchanging ecosystem. However, since data alone does not enable higher efficiency, safety or automation, the demand for data processing is constantly increasing. Thereby, specific use cases, e.g., in the field of automated driving, require high demands in terms of latency. Decentralised, intelligent systems leveraging efficient AI models and suitable edge computation platforms are currently being investigated to close the gap. These developments will contribute to the European Commission long-term strategies “Vision Zero” (reduce road fatalities to almost zero) and “European Green Deal” (climateneutrality), which should be reached by 2050. This introductory article will outline the most recent developments in autonomous passenger transportation. By doing so, we'll go into more detail about current MaaS developments in the ITS industry that are enabled by AI and speculate about potential prospects. The article concludes by summarising continuing operations related to the AI4DI project that are covered in two different publications.

1.1 AI DEVELOPMENT IN TRANSPORT INDUSTRY

AI has increasingly become a necessary method for analysing ITS-related data in recent years. This pattern, which is supported by a broad industrial base, creates a strong basis on which to construct a productive MaaS architecture. As a result, based on the survey conducted by Yuan et al., the most recent developments for machine learning (ML) applications are highlighted. The three main goals of perception, prediction, and management make up how the authors of this study organise ML applications. This distinction relates to the three main areas of study that make up the processing architecture for autonomous driving: perception, planning, and control. Perception - Due to the widespread use of modern sensors like cameras, LiDARs, and radars, the variety and volume of traffic perception data have drastically expanded. As a result, ML techniques are being used as a first step to analyse big data and extract useful information. Aspects of perception relate with the real environment (the road, cars, and pedestrians) as well as the monitoring of digital elements (the communication network's dependability and security). Earlier work on object classification, detection, and segmentation relied primarily on supervised machine learning (ML) algorithms like Support Vector Machines (SVM), which used manually created features. However, more recent trends aim to use deep learning (DL) models, which have the ability to embed features directly into their neural network architecture. Convolutional Neural Network (CNN) implementations like YoloV4 [4] are common techniques. These models tend to be more adaptable (resolution, orientation, scene) and resilient to anomalies or external variables than classic algorithms (daylight or weather). Apart from perception algorithms using a single sensor-type input, data-fusion strategies are also being developed right now. These are either high-level (several networks are employed, and outputs are subsequently concatenated) or low-level (a single model uses all raw sensor inputs for inference) [5]. and further enhance the overall reliability of the perception module. Moreover, perception algorithms fusing the output of multiple agents generating HD-maps and digital twins are research fields. For ITS to achieve prediction goals, such as predicting traffic, trip times, vehicle behaviour, and road occupancy, a variety of ML techniques are being examined. These techniques enhance fleet management decision-making, for instance in terms of the last mile assistance use case. The provided perception models' outputs are used to inform the application of traffic flow prediction techniques, which are then utilised to calculate journey times for both cars and passengers. The outcomes are then used to ultimately optimise the choice of vehicle and route on a global level. Recurrent Neural Network (RNN) architectures and its derivatives, such as Long ShortTerm Memory (LSTM), are used for these tasks because they call for a description of temporal-spatial changes.

Management - ML is thought to improve resource, infrastructure, and vehicle efficiency when used for management activities. This involves choosing a trajectory or path for the autonomous fleet as well as controlling traffic signals. Secondary objectives are addressed, including resource management for V2X communication [8] and d mobility-aware edge computing offloading. These jobs include networking and computation issues. In contrast to the prior area, deep reinforcement learning (DRL) approaches are frequently studied by machine learning (ML) for management choices. For instance, Deep Q-Learning (DQN) is thought to be the best method for managing traffic lights to reduce line wait times. Additionally, Proximal Policy Optimization (PPO) is used to steer and regulate the speed of an automated vehicle.

1.2 FUTURE TRENDS FOR APPLICATION IN TRANSPORT INDUSTRY

The following paragraph describes on two future applications utilising the introduced ML technologies in detail.

Automated driving - In recent years, commercial applications of AI have been made in Advanced Driver Assistance Systems for passenger automobiles (ADAS). Additionally, in recent years, AI has been employed in the creation of functions for automatic driving. The most popular deep learning techniques, CNN and DRL, have been effectively used in automated driving systems. It is sometimes necessary to combine various AI techniques in order to develop a fully automated driving system (ADS) that is trustworthy and strong.

One of the key needs and difficulties in creating deep learning solutions is training data. Large data sets have been gathered by several ADS developers for environment perception and autonomous driving. Fortunately, more and more open data sets are being made available to researchers. The KITTI benchmark suite [12], which consists of multiple data sets to test various ADS functions [3], is one of the most wellknown data sets for ADS development. There are several open data sets that are comparable, including Berkeley DeepDrive [15], Cityscapes [14], and the Waymo Open Data Set [13]. Since it is difficult to account for every circumstance that an autonomous vehicle can face in the actual world, the training data is always confined. However, the quick development in gathering more substantial and larger data sets will enable more advanced deep learning systems on automated vehicles.

For autonomous driving to work, the perception of the surroundings and the knowledge of the surrounding scene are essential. This involves looking out for other drivers, traffic signs, and other roadside decor. Detecting, monitoring, and categorising different types of road users, such as vehicles, trucks, buses, pedestrians, cyclists, etc., requires the use of deep neural networks, such as CNNs.

Deep learning methods for pedestrian identification have made significant progress [1]. The process of detecting pedestrians from camera data is still difficult, nevertheless, because of significant occlusions and poor weather. On the basis of camera data, deep learningbased techniques are also often employed for recognising and tracking the locations and geometries of moving objects (such as other cars).

Image segmentation is used to classify the pixels of an image into the road and non-road parts. Road marking detection and recognition involves detecting the marking positions and recognizing their types (e.g., lane markings, road markings, messages and crosswalks) [16]. Other road furniture detection includes, for example,traffic sign recognition. Environment perception algorithms based on AI only use two dimensions (2D). 2D models, however, are not always sufficient to explain 3D real-world things. LiDAR or stereo cameras serve as the foundation for 3D perception. Automated driving necessitates 3D monitoring and behaviour prediction of other road users. Vehicle behaviour includes lane changes, braking, steering, and moving trajectory. The behaviours of pedestrians include things like jogging and crossing the roadway. In the coming years, AI and ML will gradually make it possible to predict other road users' behaviour and intentions better. Prediction of traffic flow and journey times for public transportation has been done using a variety of AI algorithm combinations. Travel time forecasts help with traffic and congestion management, as well as vehicle dispatching and routing.The complicated and difficult challenge of forecasting traffic flows and travel times is influenced by a variety of elements, such as spatial correlations, temporal dependencies, and external circumstances (such as events, holidays, weather, and traffic signals) [1]. There are segment- and path-based estimating methodologies for predicting journey times. Recently, integrated DL techniques have also been investigated. These techniques combine segment-based and path-based approaches. Recently, academics have attempted to successfully merge deep learning with conventional techniques. Since most road networks do not have traffic measurement devices, training data for AI-based prediction development is difficult to come by. Mobile devices may be used to collect traffic data, and global map data suppliers like Google and Here are frequently a source of this information. Multiple data sources are frequently combined to provide better results. For precise traffic forecasts, high-quality public data sets from the actual world are crucial. These are gradually becoming accessible as open public data from various European towns. For instance, there may be several potential to create new AI-based solutions if public transportation data from a city is made available. A positioning system, such as the Global Navigation Satellite System (GNSS), is installed in the majority of public transportation vehicles nowadays. Vehicle locations, public transportation timetables, route IDs, and other information are frequently included in open public transportation data from a city. A constant open data stream of this sort has made it possible to construct ML-based ETA prediction techniques. Several external data sources, including weather, traffic, and passenger information, have recently been incorporated for the creation of machine learning models in various research.

1.3 AI BASED APPLICATION

Partners in the AI4DI initiative are developing AI and Industrial Internet of Things (IoT) technologies that have a variety of uses in the transportation industry. Two articles on the application of AI and IIoT in the transportation industry are introduced in this part. In the context of automated MaaS, they discuss issues and technology advancements for perception, prediction, and management. The article "AI-Based Vehicle Systems for Mobility-asaService Application" discusses the safe operation of automated vehicles in urban settings and makes a novel suggestion for data fusion between an in-vehicle camera and a LiDAR sensor. This method aims to improve the environmental perception to detect other road users. Deep models (high-level, deterministic, supervised, and reinforcement learning) are used to accurately recognise and track 3D objects. With encouraging outcomes, the KITTI benchmark suite has been utilised for development and validation. With the quick advancements in autonomous control technologies that provide better visual and tactile sensations, the difference between virtual and actual settings continues to narrow. The article "Open Traffic Data for Mobility-as-a-Service Applications - Architecture and Challenges" discusses the need for high-quality real-world public data sets as ITS digitization advances and the resulting requirement for data pre-processing from a variety of sources, including raw sensor data, in order to prepare for AIbased modelling. However, a system architecture is given where calculations are scaled and dispersed to various levels in the edge-cloud continuum, despite the fact that existing pre-processing is frequently implemented as a cloud solution. The development of a set of data refinement techniques has improved data integrity and quality, making the data better suited for AI-based MaaS applications.

II. FUTURE AI IS GOVERNED BY DEEP LEARNING

Deep learning innovations continually uncover the mysteries behind the vast amounts of data generated in various industries . According tothe market size of this technology was estimated at US$272 million in 2016, and its high data storage capacity, precise computational power, and ability to handle large amounts of complexity will drive growth. Expected. of data. This score is based on applying Deep His Learning to healthcare image recognition tasks and Facebook's facial recognition feature. The automotive, financial and data mining sectors also continue to improve their operations by adopting deep learning AI technologies. Furthermore, finding patterns in data for future useful predictions will make the value of deep learning soar to $10.2 billion by 2025 the authors showed that the business, economic and social value of using AI can be improved in the travel and transportation sector. They found that AI can provide greater value for modern deep learning neural networks than traditional techniques . For example, AI technology can be used to find the best and fastest routes for road users and delivery services. A European company has managed to record truck performance and driver behavior in real time by analyzing information from sensors on the road. This has reduced fuel costs by 15% and shortened delivery times. Airlines can also avoid the cost of canceled flights by using AI technology to predict weather conditions and congestion. Other benefits include reducing traffic congestion, planning the best public transport for customers, safety for drivers using self-driving cars, and improved air quality. on average. This value increases from 62% to 128% in the travel industry and 89% in the transportation and logistics industry. In the future, the use of self-driving cars will lead to the growing value of deep learning. Moreover, it is estimated that by 2030, he 30% of vehicles will be self-driving cars, reducing the cost of congestion in Australian cities from $38 billion to about $26 billion. FIG1 AFIG2

2.1 LIMITATION OF AI

AI methods have received various criticisms since their introduction in the field of transportation. One of the biggest limitations of AI is viewing ANNs as “black boxes” . This means that the relationship between inputs and outputs is established without knowledge of the internal computations of the System 4445.

Furthermore, it is suggested that ANN can generalize to case where some information is missing from the dataset. However, research has overcome this limitation by combining neural networks with other conventional techniques and other AI tools as a hybrid solution to address this problem . However, this requirement of hybridization to improve performance, especially in multi-scenarios, is seen as a general weakness. AI-based development for efficient transportation systems is very complex. This is because the creation of machine intelligence is necessary along with the correct understanding of human-based information . To date, AI applications in transportation are limited to specific his ITS applications, such as data analysis and forecasting future mobility. It would be more efficient if the AI application could handle the full range of processes. Therefore, the must exploit the full potential of AI to develop applications that can operate as a standalone system. Therefore, it is important for future research to incorporate AI knowledge into traffic analysis, data collection and storage, decision-making, and optimization modeling. Accurate and punctual predictions are unreliable when AI techniques are based on data collected in traditional ways using loop detectors, sensors, actuators, etc. It is therefore important to move from traditional data collection methods to the new AI-based technology. It provides a novel, easy-to-deploy data mining tool.Another limitation is the ability of AI raster algorithm tools (such as GA and ACO) to achieve the highest optimal solution. Moreover, mathematical computational methods, in contrast to the use of the AI-grid algorithm, allow a true understanding of the inner structure of the problem and the nature of the solution. For difficult optimization problems that are impossible using traditional mathematical methods, the fast analytical results produced by these algorithms are better than no solution. Moreover, the above studies prove that these algorithms achieve good solutions in most cases. The parameters and assumptions need to be adjusted and iterated several times to achieve the optimal solution and gain more insight into the problem.

Another limitation is the bias introduced into the training data. This is most often verified by humans who can introduce errors and biases into the labeling. In transportation, the ability to predict short- and longterm traffic flow is critical. The challenge is to anticipate unforeseen events and adverse weather conditions. Unfortunately, existing AI technology cannot handle such events and situations. Therefore, developing algorithms and forecasting schemes that respond to weather and events is critical to achieve high accuracy.

AI in the development of these algorithms will increase the efficiency of online computations and improve the standardization of spatial and temporal data coverage requirements. Most AI approaches like NNs for time series transport applications rarely integrate testing for errors and model-specific properties. 3. CONCLUSIONS This white paper provides an overview of the application of AI to various traffic-related problems. Providing the data needed to develop AI applications, the range of applications is expected to expand as cities and transportation systems become better equipped. This review highlights many applications expected to have a greater impact on future cities, including autonomous vehicles, public transport, disruptive urban mobility, automated accident detection, prediction of future traffic conditions, and traffic management and control. focus on the field. It shows how AI can be used to solve challenges such as increasing travel demand, CO_2 emissions, safety concerns, and fuel waste.

publications describe how AI is effective in designing and developing optimal networks for communities, finding optimal public transport schedules, improving traffic light schedules, and optimizing routes forindividual drivers. There are many case studies showing It also applies to automatic event detection, inflight anomaly detection, and image processor/video sequencing of data collected on the road. In recent years, AI has also been developed for use in traffic demand forecasting, management and control using forecasts of weather conditions and future traffic conditions, and quick decision-making in traffic jams and dangerous situations. B. Reduce traffic accidents. It also helps authorities decide whether to add new infrastructure, extend lanes, which route to take in the event of an accident or severe weather, and how much money is needed for maintenance and repairs. Additionally, automated vehicles and automated public transportation systems are increasingly benefiting from AI tools to avoid disruptions, accidents, and traffic jams. We also addressed key limitations of AI, especially the perception that neural networks are “black boxes” and the biases in training data resulting from humans labeling training samples

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