Machine Learning for Autonomous Vehicle Real-time Traffic Monitoring and Analysis

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1. Introduction to Autonomous Vehicles and Real-time Traffic Monitoring

This paper intends to provide a state-of-the-art literature review that covers topics pertinent to autonomous vehicles and real-time traffic monitoring and analyse research relating to these areas. Several autonomous vehicle topics were recognised including, but not limited to the following: fine pattern concerning the simulation, validation research and control techniques for unexpected autonomous vehicle movement, disaster response considerations and their enhancements, a Pavelbravo obstacle avoiding algorithm, ant colony system improved technical strategies and implementation plan development for sub-micrometer precision. Moreover autonomous vehicle topics were found influencing real-world visions, delivery traffic organisation, an everyday modification of car sales and traffic accident forecast. This review finds an analysis of contemporary research across these pertinent areas can be used to identify knowledge challenges and potential measures to overcome such challenges.

In recent years, driving environments have become rife with uncertainties, and there is significant room for improvement in the field of transportation and safety. With the rapid advances in Artificial Intelligence (AI), particularly with powerful tools such as deep learning (DL) [1], there is significant progress and potential in traffic safety, with man-made intelligent advanced driver systems, autonomous vehicles and autonomous drones in a broad area of scenarios becoming capable of driving people, carrying goods and assessing road conditions under a range of various weather conditions. Among particular 'traffic accident alarm system'-focused improvements, real-time traffic monitoring is a fundamental technology, which is concerned with a situational awareness characteristic for detection of accidents in the presence of obstacles/technical weaknesses, perturbations (e.g. floods or hackers' attacks) and changing users' habits, which usually emerge in city traffic due to COVID-19 restrictions or punishment/deterrence traffic policies in the environment-not-friendly areas and cutting speed restrictions in the friendlier city environments.

2. Fundamentals of Machine Learning in Traffic Analysis

Once a model is trained, it is common for it to be deployed in smart traffic infrastructure dedicated embedded computers in intersections/virtual traffic lights, autonomous vehicle control systems, intelligent video cameras, onboard computers in public transports, etc. There are significant concerns and limitations present in such implementations for ASS. These systems require real time inferences with respect to the collected video data from the sensors within a limited computational power. Additionally the deployment platform is limited with respect to the weight and dimensions. Furthermore real time and autonomous/remote updates/improvements are needed to enhance the ASS functionalities and the collected data. [2] The huge developments in intelligent edge computing hardware, deep learning software such as TensorFlow Lite, neural network pruning techniques, as well as distributed and shared learning approaches have enabled implementation of highly accurate ML solutions with low inference computational power on the embedded systems. Systematic approaches have been proposed in the literature to solve the above mentioned issues in the literature.

Traffic flow is stochastic due to the driving style and the changing weather/road conditions. In addition, the system's dynamics, i.e..engine characteristics, gearbox dynamics, braking and turning aspects are nonlinear. Therefore, model-free data driven artificial intelligence (AI) and machine learning (ML) solutions are considered for ITS instead of conventional model-based control theory. Deep learning-based intelligent sensor-based applications are increasing recently as these approaches are better suited to the task due to the self-learned feature extraction and a better fit with the human brain and neural networks. Data is collected from the connected sensors for use with the ML algorithms to make automatic decisions and optimizations. In the ITS and ASS applications, the currently popular ML algorithms in research are the convolutional neural network (CNN) family.

[1] [3] Traffic analysis is key to smart city development, especially in view of future autonomous vehicles. Traffic data directly and indirectly affect citizens' safety, transportation system efficiency, pollution generation, and urban designs in a global context. One of the main reasons for traffic accidents is human error in driver behaviour. Therefore, one of the main goals of intelligent transportation systems (ITS) is to provide smart and intelligent traffic

infrastructure that can minimize human involvement in transportation. Intelligent sensor-based applications (ISBA) such as autonomous vehicles, traffic light controlling, congestion pricing, and video surveillance require real-time accurate traffic monitoring.

3. Data Collection and Preprocessing for Real-time Traffic Monitoring

The intelligent monitoring tools that are inspired by the traffic surveillance process, we present a new automated traffic monitoring system consisting of three main parts [4]: RTA, DTSM and LTVM. The data collector RTA is responsible for gathering real-time traffic analytics (RTA) by analyzing digital video footage perceived by the surveillance cameras. This traffic analytics is used by the traffic anomaly detector DTSM to alert in real-time the Traffic Management Centres responsible of traffic control of any traffic abnormalities. The Long-Term Video Monitoring LTVM part of the system is used for seeing the long-term observations of historical traffic data analytics, where data can give advance traffic knowledge by forecasting traffic congestion events. The data voices coming out from the traffic anomalies detector are repeated every 10 s. After each voice the system is in pause mode for 55 s [5]. Therefore, the system is configured to alert the TMCs at any time after that any traffic congestion has occurred.

Real-time traffic surveillance is a fundamental component for efficient traffic analysis and control. This is achieved in many Smart Cities around the world using traffic cameras spread in different locations [6]. These traffic monitoring cameras produce huge amounts of video footage to be watched manually for certain periods or triggered manually by an event for a specific camera. Traffic data monitoring poses challenges such as processing large quantities of data in different modalities including raw video footage from traffic cameras and associated meta-data with public knowledge like weather information and historical traffic data, and general knowledge about traffic for automatic decision and reasoning to be answers for given queries. Manual surveillance of traffic is focal and time-consuming; today, manual monitoring and reporting of traffic abnormalities such as congestion and accidents are the typical surveillance systems.

4. Supervised Learning Techniques for Traffic Flow Prediction

The road traffic data are the framework of all the road traffic monitoring and control systems used in today's cities. All these systems process historical and real data sets and are supported by various prediction models [7]. The base of the urban traffic model is a modified space-basket model existing in the literature. In this work the spatiotemporal dynamics of a city road network is analysed with the help of a spatiotemporal road traffic state representation method.

Combating road congestion is a major ICT application area. To optimally utilize road infrastructure with high accuracy, real and instant information on the road conditions is an essential requirement [8]. The pre-requisites of road traffic models are the outputs of these detectors, which may include average speed, number of vehicles, vehicle classification, or road occupancy. These data streams are then resumed in Discrete-State Continuous-Time (DSCT), Continuous-State Continuous-Time or discrete-time. However, the velocity is the main data stream used for real-time traffic monitoring and data analysis in this framework [1].

5. Unsupervised Learning for Anomaly Detection in Traffic Patterns

Unsupervised learning is the technique for anomaly detection. The connections among the units of neural networks are adaptive; they are changed so that the network rapidly adjusts its inputs to produce the desired outputs. Once the network has been trained, an output for a given input is produced within reached level so that fitness functions are minimized; the error is made in predicting changes of the input. The network then reconstructs the input pattern so that it accurately represents as a response. The level of prediction error is used to detect anomaly. K Nearest Neighbor from the basis of distribution affords metric to observe anomalous pattern [9].

Vehicles are required to obey traffic rules to ensure a smooth traffic flow; however, in the presence of some anomalies (e.g., accidents, bad road conditions), traffic jams are common. One may split up vehicles into various groups such as cars, trucks, buses, autos, etc. to analyze traffic patterns. Traffic monitoring using motion templates of the background scene stripes paintings from the observed scene sequence may identify the anomaly because the trajectory that contains an anomaly behaves quite differently from the normal. In this study, the Stripes Painting of the Background Scene, namely motion template, is computed in a data-driven fashion adopting the auto-encoder approach [10].

The rapid expansion of urban networks has necessitated the deployment of a real-time monitoring and surveillance system to ensure incident-free commutes within cities and on highways. The growth in the traffic volume across roads in cities and highways, as well as the growing dependence of the economy on the road transport system, highlights the need for a capable and effective system with the goal of ensuring event-free commutes. The goal of the surveillance system is to keep track of the overall traffic behavior—identifying and mapping various traffic incidents such as vehicle accidents, aggressive human behavior (road rage), wrong parking, and danger to pedestrians, and keeping track of events such as artificial traffic congestion [11].

6. Reinforcement Learning for Autonomous Vehicle Decision Making

In recent years, with the rapid development of artificial intelligence (AI) technologies in various applications, RL has drawn increasing attention. RL is an advanced machine learning method in AI that an agent takes actions in a sequence of states at different times to achieve overall optimal results, based on interaction with the surrounding environment. The agent can learn new strategies gradually and adapt them to the system environment. The RL agent is optimized for driving environments, and the autonomous vehicle is able to learn global driving strategies and optimal policies, which makes it very suitable for the decision-making design of autonomous vehicles. In the last decade, different algorithms for solving the RL problem and several consolidated topics, such as value functions, exploration/exploitation trade-off, and off-policy credit assignment with eligibility traces, that remain topical, have been discussed in depth. RL has achieved considerable achievements in various AD scenarios, such as lane-changing maneuvers, traffic light overtaking, vehicle edge overtaking, roundabout pass, reverse recovery, and parking, so the training phase is able to cover driving domains suitable for new drivers. Different AV applications of RL, especially state-of-the-art deep RL, will be introduced in detail. Integrations of different POMDP representations of the AV engine and RL tools will open new challenges for action selection strategies and evaluation of the AV control framework choices.

[12] [13]To make reasonable decisions in different driving environments, it is important for an autonomous vehicle to learn strategies in an adaptive and intelligent way. In the process of making this decision, the vehicle needs to consider various factors in a complex and uncertain environment, price information and maintenance costs for the decisions made and

learn the long-term impact of different behaviours on the cost or risk of accidents. Traditional planning and decision-making algorithms such as Dynamic Programming (DP) and graph search are difficult to apply directly in this context due to the high-dimensional state, complex dynamic constraints, and various types of uncertainty existing in the wayfinding process, directly causing the scalability problem of the algorithm. Moreover, human engineers are required to exhibit domain expertise to model or design specific features of the state space and definite modelling parameters. However, in the automotive applications, features of the environment are often complex, the algorithm needs to deal with complex dynamic constraints such as nonlinear and discrete state spaces, high-dimensional state spaces, and various types of uncertainties, which are specifically difficult to deal with by traditional algorithms. Reinforcement learning (RL) is one of the most effective learning algorithms to address the autonomous vehicle decision-making process. The basic model includes a vehicle decision maker (optimal system policy) and a vehicle environment where the policy observes states and returns actions, and the vehicle receives driving revenues.

7. Deep Learning Models for Traffic Image Recognition

[14] [15]The automation of traffic enforcement systems in the context of monitoring congestion or the performance of a specific facility allows to carry out road interventions or propose alternative routes in a quickly and efficient way. In this sense, the work of Zong et al. is in broad agreement with ours.[2]Regarding the area of autonomous vehicle, Sudharsan et al. similarly emphasize the importance of RGB-D camera sensors for the detection, classification, and tracking of the traffic. Furthermore, the combination of Lidar and camera data is being used to infer 3D information. However, the main the aim of the present work is to create an efficient module to robotic vehicles, from visual sensors, achieve real-time detection, classification and tracking of traffic without needing further equipment, which can be used and easily integrated into most real-world scenarios.

8. Integration of Machine Learning with Sensor Networks

The proposed architecture has been implemented and validated for several typical scenarios and has been shown to be efficient in terms of accuracy, precision, recall and absolute errors. In the future work, the authors plan to study and extend the proposed architecture to air, land and space autonomous vehicles in both direct and edge offloaded processing systems. In the study [16], a machine learning model, specifically deep neural networks, has been proposed to provide a solution to the challenge of aging vehicular networks. The proposed model, in contrast to existing work, utilizes the available log data of the dynamic features of the vehicles. The presented neural network structure was trained to forecast the states of the simulation chain of three vehicular network mobility metrics, node lifetime, end-to-end delay and packet loss rate, over different time slots which contain the vehicle dynamic behavior and contextual information. The proposed model has the flexibility to be switched on at runtime to preserve the useful resources on the vehicle.

Traffic monitoring mainly depends on sensor networks, which can be used for detecting traffic. In [17], the authors proposed a two-tier architecture for data pre-processing and real-time traffic detection based on continuous data streams from sensor networks. The first tier starts with the pre-processing of raw AIS data, followed by data enrichment, data quality improvement and micro-aggregation. The second tier focuses on the real-time processing of the pre-processed AIS data to extract traffic speed, traffic direction, traffic location and traffic status by means of AIS messages evolution.

9. Challenges and Opportunities in Real-time Traffic Monitoring

Deep learning approaches are basically used to solve the classification, object detection, tracking, phenomena detection, and predicting the future congestion problem. The DNN and the Long Short Term Memory (LSTM) based traffic classification and traffic regression models are proposed to monitor the congestion and the traffic classification problem. The real-time vehicle monitoring fusion model is considered for the vehicle counting, vehicle speed estimation, real-time vehicle classification system, and vehicle tracking problem's solution. Additionally, the proposed research work aims that the traffic congestion estimation approach under the cognitive Unified Data Analytics (UDA) framework of the CNN fusion approach can also monitor any challenging environment. The MELT evaluation framework is also applied to the real-time traffic CNN model under different fog environmental categories. Due to the CNN integrated real-time freeway video webcam monitoring, the real-world collected Malaysian datasets of the non-fog and the fog of the edge competition and the NPFog datasets are implemented in this research study. In the dimensionality descriptors investigation, CNN-based automation envisioned models' intelligent performance in both the fog avoidance and energy generation environments.

Additionally, in terms of autonomous driving, a human-like decision-making processing using Neural Network (NN) is proposed based on a Convolutional Neural Network (CNN). Graph-based traffic analysis is used to monitor high-speed camera signals. Traffic monitoring methods effectively analyze the traffic impact response for reliable traffic monitoring. The real-time traffic monitoring and analysis are essential to provide the efficient vehicular mobile services and intelligent transportation system. When the real-time traffic signal detection, classification, and segmentation is also an essential challenge in the field of the real-time traffic monitoring and analysis. As such, many advanced machine learning (ML) based traffic monitoring techniques are investigated in recent years. [18] For example, Deep Neural Network (DNN), Generative Adversarial Network (GAN), Recurrent CNN, and Generative Adversarial Network (GAN) based automatic traffic light signal detection, classification, and monitoring and events detection is proposed in, followed by rule-based and camera network structure-based real-time traffic congestion alleviation approach is proposed in. In, cellular optimal traffic signal scheduling system in the real vehicular mobile system is monitored for the energy-efficient vehicular communication through provision of the compression methodology. An automatic real-time traffic light signal extraction from camera image traffic junction monitoring is proposed in. Moreover, Reinforcement Learning (RL) is used to solve environment action and state problem in the real-time traffic signal monitoring in. And also a new technology is presented in, which is a real-time traffic light monitoring system, which can manage energy and computing resources at the same time. Additionally, a deep reinforcement learning-based vehicular traffic monitoring and tracking approach under the hybrid V2X communication environment is also previously proposed in. However, the real-time traffic monitoring and analysis issues through the freeway sensor fusion of the CNN also consider the fog environment types.

[19] Machine learning (ML)-based techniques, such as neural network (NN) models, are highly effective in vehicular applications for real-time traffic monitoring. Traffic sensing and monitoring have been broadly used for traffic management and structural health monitoring. In autonomous driving, automatic detection and signal extraction are very useful for real-time traffic detection and monitoring. Self-modeling filters may distinguish the pollution impact from the real-time or background residuals. Supervised, unsupervised, and reinforcement learning are the main types of ML. Moreover, times series–based, spatial relations–based, and neurovisual relations–based vehicle detection, tracking, and classification approaches

(namely, visual ML) are used to detect and classify vehicle classes in the surveillance environment.

10. Case Studies and Applications in Autonomous Vehicle Traffic Analysis

Several autonomous vehicles' traffic monitoring techniques and concepts are presented, such as monitoring and controlling the speed of intelligent vehicles, monitoring connecting bus lines, monitoring high-quality Internet of Vehicles (IoV), driver characteristics extraction, and joint recognition of human–vehicle traffic flow state using the characteristics of areas in smart city intersections. The main motivation for involving machine learning and robotics for autonomous vehicle traffic real-time monitoring and analysis is to predict and detect vehicles that move in violation of traffic laws and do not follow traffic rules. The proposed system was trained with real-world traffic data and involved different robotic algorithms, measuring the lifetime of vehicles on an intersection area. Another significant learning-based traffic monitoring system was implemented for connecting buses in large cities [19]. This time-efficient autonomous system integrated novel convolutional neural networks to solve a real-time problem. For implementing this intelligent system two relatively compact and highly efficient deep CNN models, wherein one model was used for detecting connecting buses, and another for counting the number on each connecting bus line respectively. Such vehicles can carry thousands of passengers on a daily basis, so it is important that they are managed effectively. The positions of the connecting buses, as well as their routes, are detected by using a camera module operating in the infrared spectrum. Furthermore, the Brazilian traffic regulations were used to define the average speeds of the buses on each connected line. Finally, educating institutions, government, public institutions, businesses, owners of autonomous vehicles and the public in Post-Covid-19 periods are suggested. The level of alertness of drivers who have adapted to traffic regions that have become quieter will have dropped to dangerous levels. Such drivers, and occasionally wild animals, represent a severe danger, especially on urban roads. For these regions, the system proposes the concept of "traffic first aid" – in which the recommendations in the domain are transferred into a Cloud service and stored for its users. Later on, these alerts can be transferred to any autonomous vehicle's Digital System during the planned routes [20].

Traffic monitoring and management in autonomous vehicles are surveyed in this section. Two general strategies exist for monitoring systems in autonomous vehicles. The first strategy involves using data from an Automatic Identification System (AIS) integrated into autonomous vehicles, or installed in the traffic network, for collecting and reporting control signals, navigation data, vessel's identity, and/or position and motion-related data to a server [17]. From this data, machine learning models are trained and deployed that further analyze the traffic data based on their capabilities for enhanced traffic surveillance and management. The second strategy uses image detection from various sources including RGB cameras, satellite images, and video with increasing implementations of deep learning technologies for traffic monitoring and management.

11. Ethical and Legal Implications of Machine Learning in Traffic Analysis

Connecting authorities, academia and industrial institutions, as stakeholders, in the most crucial aspect of the next generation AVs. This would lead to a framework for a balanced development in the automotive industry, where each party, either the manufacturer, driver, or intermediary bodies, has the possibility to benefit equally. However, drawing appropriate norms of conduct, and positively influencing both local and national road mappings, while also reflecting them on the international level, should be scrutinized thoroughly. In this respect, it should be noted that lawful norms, principles and regulations will be critical in the determination of investment strategies and the setting of competitive targets for the actors within the sector. We must ensure interoperable AVs for global markets, and avoid international conflicts over the control of technological standards. Therefore, as a necessary first step, it is our obligation and responsibility to discuss in detail the ethical and legal framework that we will apply to the pre-production and the intraspecific usage of AVs. [21]

[A code] Given the increasing demand and advancements in Automated Vehicles (AV), attention has turned to road traffic optimization to ensure state-of-the-art traffic flow. Autonomous vehicles (AVs) need to learn collective drivers' behaviors and develop cross-relationship databases for safe and adaptive function. The databases should include data related to various situations and user behaviors. Each of these situations also have hypothetical, ethical and real-life consequences. Therefore, it is important to systematically collect these data and analyze complex relationships between driver behaviors prior to commercializing AVs based on the relevant law. On the other hand, the analyses carried out may foster ethical and legal consequences. [22]

12. Future Research Directions and Innovations in Autonomous Vehicle Traffic Monitoring

Similarly, Future Research Directions and Innovations in Autonomous Vehicle Traffic Monitoring and Analysis:VMs and commercial fleets could benefit from the developed technologies and methodologies presented in this chapter. Regarding the work presented in this chapter future research are first focused on improving the performance of the detection methods. In road traffic, anomaly data are rare data; particularly in terms of learning, the generalization will be poor, Cs contain robust detection frameworks, and defining the anomaly and applicable constraints to the methods are some of the challenges. To enhance the detection of the anomalies, the collaboration of cameras with other sensors within the vehicle is a logical approach. Being capable of detecting traffic anomalies, a microsimulation platform should be used in an interactive manner. This important platform might be forced to consume significant computational resources during the execution time and suffers from control algorithms unable to act quickly to alleviate the congestion. Also, the control algorithms should be able to take non-optimal control decisions to avoid the congestion. Therefore, the second improvement must optimize the near real-time mutual control and decision sharing between the management and control layers. Coordination of these two layers through collaborative traffic management and the most influential coordination strategies are the two subjects which are not yet developed in the current traffic signal control systems are required as future research directions. In order to let machine learning analysis not only cameras but other sensors and to act more intelligent, recent technologies of machine learning application in sensor data should be a focus in future works.

[23] [24]To enhance the autonomy of future connected and autonomous vehicles, and to enable them to interact safely according to the standards of vehicle-to-everything (V2X) communication, more comprehensive real-time traffic monitoring and analysis are crucial for two reasons: first, a high level of understanding of the dynamic environment allows vehicles to foresee the flow of vehicles or mitigating affected advisories, which can effectively avoid congestion, improve traffic efficiency, and enhance the comfort of vehicle driving. However, current traffic monitoring systems are not able to provide real-time; accurate, and high-quality traffic condition information, which greatly limits the traffic planning of the next-generation transportation systems. Of particular significance, intelligent transportation systems representatives of today’s traffic control centers, public transports, and commercial fleets.

References:

1. [1] Y. Zhu, M. Wang, X. Yin, J. Zhang et al., "Deep Learning in Diverse Intelligent Sensor Based Systems," 2022. ncbi.nlm.nih.gov
2. Mahammad Shaik, et al. "Envisioning Secure and Scalable Network Access Control: A Framework for Mitigating Device Heterogeneity and Network Complexity in Large-Scale Internet-of-Things (IoT) Deployments". Distributed Learning and Broad Applications in Scientific Research, vol. 3, June 2017, pp. 1-24, https://dlabi.org/index.php/journal/article/view/1.
3. Tatineni, Sumanth. "Beyond Accuracy: Understanding Model Performance on SQuAD 2.0 Challenges." *International Journal of Advanced Research in Engineering and Technology (IJARET)* 10.1 (2019): 566-581.
4. Vemoori, V. "Towards Secure and Trustworthy Autonomous Vehicles: Leveraging Distributed Ledger Technology for Secure Communication and Exploring Explainable Artificial Intelligence for Robust Decision-Making and Comprehensive Testing". *Journal of Science & Technology*, vol. 1, no. 1, Nov. 2020, pp. 130-7, https://thesciencebrigade.com/jst/article/view/224.
5. [5] D. Impedovo, F. Balducci, V. Dentamaro, and G. Pirlo, "Vehicular Traffic Congestion Classification by Visual Features and Deep Learning Approaches: A Comparison," 2019. ncbi.nlm.nih.gov
6. [6] E. Qasemi and A. Oltramari, "Intelligent Traffic Monitoring with Hybrid AI," 2022. [PDF]
7. [7] M. Aqib, R. Mehmood, A. Alzahrani, I. Katib et al., "Smarter Traffic Prediction Using Big Data, In-Memory Computing, Deep Learning and GPUs," 2019. ncbi.nlm.nih.gov
8. [8] S. Almeida Carneiro, G. Chierchia, A. Pirayre, and L. Najman, "Clustering Dynamics for Improved Speed Prediction Deriving from Topographical GPS Registrations," 2024. [PDF]
9. [9] D. R. Patrikar and M. Rajaram Parate, "Anomaly detection using edge computing in video surveillance system: review," 2022. ncbi.nlm.nih.gov
10. [10] G. Kim and S. Kim, "A Road Defect Detection System Using Smartphones," 2024. ncbi.nlm.nih.gov

11. [11] S. Bakheet and A. Al-Hamadi, "A deep neural framework for real-time vehicular accident detection based on motion temporal templates," 2022. ncbi.nlm.nih.gov
12. [12] S. Kuutti, R. Bowden, Y. Jin, P. Barber et al., "A Survey of Deep Learning Applications to Autonomous Vehicle Control," 2019. [PDF]
13. [13] S. Malik, M. Ahmed Khan, H. El-Sayed, J. Khan et al., "How Do Autonomous Vehicles Decide?," 2022. ncbi.nlm.nih.gov
14. [14] J. Azimjonov, A. Özmen, and M. Varan, "A vision-based real-time traffic flow monitoring system for road intersections," 2023. ncbi.nlm.nih.gov
15. [15] X. Wang, "Vehicle Image Detection Method Using Deep Learning in UAV Video," 2022. ncbi.nlm.nih.gov
16. [16] H. Ye, L. Liang, G. Ye Li, J. B. Kim et al., "Machine Learning for Vehicular Networks," 2017. [PDF]
17. [17] J. Felipe Restrepo-Arias, J. William Branch-Bedoya, J. Andres Zapata-Cortes, E. Giovanny Paipa-Sanabria et al., "Industry 4.0 Technologies Applied to Inland Waterway Transport: Systematic Literature Review," 2022. ncbi.nlm.nih.gov
18. [18] B. Neupane, T. Horanont, and J. Aryal, "Real-Time Vehicle Classification and Tracking Using a Transfer Learning-Improved Deep Learning Network," 2022. ncbi.nlm.nih.gov
19. [19] Y. Yang, T. Dwyer, K. Marriott, B. Jenny et al., "Tilt Map: Interactive Transitions Between Choropleth Map, Prism Map and Bar Chart in Immersive Environments," 2020. [PDF]
20. [20] A. Alhilal, B. Finley, T. Braud, D. Su et al., "Distributed Vehicular Computing at the Dawn of 5G: a Survey," 2020. [PDF]
21. [21] L. Mora, X. Wu, and A. Panori, "Mind the gap: Developments in autonomous driving research and the sustainability challenge," 2020. ncbi.nlm.nih.gov
22. [22] A. Razi, X. Chen, H. Li, H. Wang et al., "Deep Learning Serves Traffic Safety Analysis: A Forward-looking Review," 2022. [PDF]
23. [23] L. Zhang, X. Yu, A. Daud, A. Rashid Mussah et al., "Application of 2D Homography for High Resolution Traffic Data Collection using CCTV Cameras," 2024. [PDF]
24. [24] M. Tiezzi, S. Melacci, M. Maggini, and A. Frosini, "Video Surveillance of Highway Traffic Events by Deep Learning Architectures," 2019. [PDF]