Machine Learning for Autonomous Vehicle Traffic Congestion Prediction and Mitigation

By Dr. Subbarao Mukhopadhyay

Professor of Electrical Engineering, Indian Institute of Technology Delhi (IIT Delhi)

1. Introduction to Autonomous Vehicles and Traffic Congestion

Estimates reveal that the worldwide economic loss caused by traffic congestion is at least $100 billion in 1980 and has very high growth annually until now. Spreading congestion prevention strategies has become a potential perspective for the widespread acceptance of AVs. In the automotive memory system, there are two ways, i.e., complete memory and gradual memory. Since the complete memory system cannot cope with generalization, the overwhelming majority of architectures now use a memory map with partial memory architecture. These techniques can significantly improve the AV's ability to understand traffic and learn driving strategies. Additionally, the traffic congestion problem is one of the most significant social challenges that the AV traffic system can help solve. Merged with AVs, a clear mobility system will make it possible to predict the state of the traffic congestion in advance and to plan for both travelers and vehicle controllers to make a detour to avoid congestion, which will seriously alleviate the traffic jam situation. In addition to affecting processing forecasting, the ability to predict traffic conditions can significantly reduce CO_2 emissions.

The advancement in transportation technology has seen a significant shift from traditional human-controlled vehicles to the development of autonomous vehicles (AV). Because transportation has a significant relationship with society and economy, the autonomy of transportation system carries immense importance. Among many of its values, the reduction/elimination of human errors, traffic jam reduction, economic benefits, reduction in greenhouse gas emissions and self driving are particularly noticeable in the AV system. The path planning function of AV is generating the most interest. The AV system predicts where the congestion occurs and provides the optimized detour route devoid of congestion, which can greatly optimize the control efficiency of AV traffic system [1].

1.1. Overview of Autonomous Vehicle Technology

Cooperative adaptive cruise control (CACC) combines the efficient traffic flow of platooned vehicles on highways (with relatively sparse urban area density) with the safety of individual human-driven cars in cities and crowded areas. Smart platoons can exchange data on vehicle trajectories, suggested speeds, and agreed passing protocols [2]. Holistic intelligent transportation systems in the near future may incorporate more data sources on better roads, suggested future traffic light status, and road geometrical and road surface information. Policymakers are looking toward improved access to road networks, fast, safe, and flexible power charging for clearing greenhouse gas emissions, and multimodal public transportation with synchronized scheduling.

Autonomous Vehicle (AV) features and technologies are rapidly advancing with the development of intelligent traffic systems that support efficient traffic management, avoid collisions, reduce fuel consumption, provide connectivity, and assist with parking. These vehicles are designed to either support the driver, known as Level 1/2 automation (partial automation) as per the Society of Automotive Engineer (SAE), or drive completely autonomously in all conditions, known as Level 5 automation [3]. The European Union directives and regulations for type-approval and safety of hybrid and electric vehicles already allow Level 2 or partial AVs on smart roads. Several challenges need to be resolved to deploy fully automated and smart vehicles under various dynamic background and environment situations, including legal issues, driver displacement, technology infrastructure, and the lack of safe mechanisms for direct communication between all road users and external infrastructure. The Internet of Vehicles (IoV) paradigm lays the foundation for heterogeneous V2X communication, thereby allowing buyers to enjoy very high levels of automation, and it may also enhance road mobility, efficiency, sustainability, and social aspects such as travel comfort, cost reduction, etc.

1.2. Impact of Traffic Congestion on Society and Economy

In addition to societal costs, excess delays in transit or access can cause extensive economic damages and have negative effects on business sustainability. Congestion issues can cost trucking companies and carriers hundreds of millions of euros per year, as congestion is reducing vehicle use and fuel efficiency. For similar reasons, on-time deliveries are not possible, so shipments are also being delayed. When high priorities such as medical attainment or perishable goods, for instance, are considered (e.g., cancer patients, fresh fruits, vegetables, meat), the delays can lead to extremely high losses. Based on a survey that was made in 2013 by American Highway Users Alliance, a traffic congestion costs one filled car and caused to seven minutes delay on route in average in U.S. highways. It was also stated that those figures also correspond to a $101 billion economic loss annually.

Traffic congestion is an aging problem that is still highly relevant [4]. It is defined as a situation where the demand for transportation systems (e.g., intersections, roads, highways) exceeds the infrastructure capacity [5]. Congestion can be recurrent, non-recurrent or due to repair and maintenance operations and similar infrastructural issues. Specifically non-recurrent congestion—which includes special events, weather, accidents, and so on—is highly unpredictable and difficult to estimate or forecast. All forms of congestion lead to several societal and economical losses. When personal or public transportation fails to deliver services as fast as consumers expect or as commuting times become longer, it causes personal dissatisfaction, low productivity and many similar problems.

2. Fundamentals of Machine Learning

Traffic congestion kills people directly in the case of accidents and in the case of air pollution, indirectly. It causes losses for the economies of many countries due to the amount of time people spend in traffic and due to industrial waste. Except for emergency situations such as bad weather conditions or accidents, traffic congestion is usually due to inefficient or lack of management in traffic systems. By using traditional methods, forecasts for traffic congestion and vehicle behaviors during congestion time are not always realized accurately and not quickly enough. Yet, enough numbers of vehicles are already in the network among whom lives and urgent situations. [6] [7]

Traffic congestion, a major contributor to traffic safety, crime, air pollution, and economic losses, can be unpredictable and presents issues for years to find accurate, simple solutions. This paper deals with driving predictive models for self-organizing, adaptive, and cognitive Intelligent Transport System (ITS) to improve traffic signals. It outlines the development, execution, and evaluation of real-time machine learning models for vehicle queue length and on-road vehicle count predictions. The functional system performs real-time sensing, observational data collection, decision support displays, and contextual traffic information frames per signal state, and predictors for predicting vehicle queue lengths and on-road vehicle counts at signalized intersections.

2.1. Types of Machine Learning Algorithms

In this paper, we focus on a class of feature-based learning models (shallow models), including (i) statistical models, (ii) traditional machine learning models based on shallow models, and deep models, including (iii) DNNs, (iv) CNNs, (v) RNNs, and deep combinations of DNNs, CNNs, and RNNs, among others [8]. i) Statistical Models: Most models in this category are univariate time series models, among which two of the most common ones are the autoregressive integrated moving average (ARIMA) models and Kalman filter (KF) models. Beyond these, the authors focus on the use of recurrent or bi-directional neural networks and temporal convolutional network for short-term traffic flow prediction. In, authors proposed seven types of deep models using feedforward neural networks, convolutional neural networks, recurrent neural networks, graph neural networks, generative adversarial networks, clustering, or a combination of two types of models as either deep fusion architectures or supervisory architectures. Both shallow models and deep models are further discussed based on the features or data inputs.

[9] Machine learning algorithms can be largely divided into feature-based learning algorithms and nonfeature-based learning algorithms on the basis of underlying algorithmic assumptions [10]. Feature-based learning algorithms use a particular feature representation of the source data value or its transformation, whereas nonfeature-based learning algorithms can deal with raw data without assuming any particular representation. The former further has two subcategories: shallow models and deep models. Shallow models require hand-crafted features, while deep models can automatically construct feature representation from raw traffic data. The authors in provided a comprehensive literature review of traffic speed prediction using deep learning techniques (e.g., variational autoencoder, hybrid convolutional and recurrent network, generative adversarial network, and stacked autoencoders). It is believed that strategies inspired by the human brain, especially the visual cortex, can effectively preserve complex spatial–temporal correlations. For instance, convolutional layers are employed to capture local spatial dependencies.

2.2. Data Preprocessing and Feature Engineering

[11] [12]From smart city intelligent transportation systems to individual mobile devices, traffic prediction and management are essential for the welfare of cities and their occupants. For example, mobile devices can be programmed or preco nfigured by their users to adapt in

situations that are beyond their processing capabilities. Special configurations may occur based on observed locations, environments, times, and working relationships with other devices. Meanwhile, intelligent transportation systems allow monitoring of roads and traffic in intelligent traffic management and control systems, prevention of traffic conditions by regulating traffic lights and signal systems, and prevention of environmental conditions by controlling ventilation systems such as tunnel pres-sure systems.[13]Most of the other road traffic management system solutions mostly focus on the aspects of optimizing individualised route advice systems based on traffic density observations, searching for parking places within the city, or more technical improvement in vehicles (eg, energy-efficient driving, autonomous driving). On the other hand, traffic congestion warning and avoidance are other major roles of the On-Board Unit (OBU) in BSCTS. In addition, a recommender system assist the drivers in selecting an optimal action plan between believing the suggested route as Informative, interpreting the route as a regular suggestion (which can be modified), and asking for a new route plan.

3. Data Collection and Processing for Traffic Congestion Prediction

The sensed spatiotemporal data from several sources or sensors, such as inductive loop detectors, Global Navigation Satellite Systems (GNSS) (or GPS), and cameras, are categorized into two types: the performance data (e.g., travel time, traffic volume, and vehicle speed) and traffic prediction (e.g., traffic density, congestion, and state estimation). There are different strategies for data collection and processing that aim to improve the reliability and integrity of the real-time traffic state. Recently, with the increased interest in mobile phone applications and ride sharing companies, many researchers used the GPS probes to get the real-time traffic data. The GPS and travel survey data are used for the traffic studies and are combined with the underlying algorithm to predict travel patterns and user mode choice and to determine which urban spaces are serving users. The collected probe GPS data is prone to noise and missing data; therefore, noisy GPS data are corrected and missing data are inferred. One such method proposes a Gaussian Mixture Model- based hybrid density filter for a multi-model estimation of multiple vehicle estimation. Encompassing heterogeneity aware probabilistic map matching method for vsNDS; it also performs probabilistic congestion analysis. The exploratory of urban transport system: traffic congestion detection and prediction with GPS-Named Data Networking based vehicular ad hoc networks and fine-grained hybrid vehicle re-routing based upon vehicular ad-hoc networks for traffic congestion avoidance is proposed. In conclusion, any complete and reliable traffic data sensing, collection, encoding, and prediction can positively affect urban transport management by tackling relevant urban transport problems. Recall that the task at hand is to detect and learn the traffic performance from historical and real-time traffic and meteorological performance. For these purposes, we need a lot of real-time and history traffic flow, traffic speed, traffic volume, and other relevant dimensional and environmental data. For the driver demand and navigational suggested route information, the Global Positioning System (GPS) provides guidance, maps, advices, and routing for the driver. GPS is used to record and store the locations of cars or mobile phones providing user location to particular coordinates in real time. It is also used to save the track files of some cars or mobile phones suggesting the X and Y location in data warehouse, oracle or or teradata database.

Traffic congestion is a core problem of the modern urban transportation system. Unlike traffic congestion in the traditional sense, which were predominantly related to excessive population and deficient urban transport resources, the modern urban areas encounter more difficulties from traffic disaster. In some cities, the urban transport network reaches the limits of its capacity and the traffic disaster phenomena, such as traffic jams, increased number of accidents, and degraded travel time predictability, are significantly affecting the urban economy, environment, and livability. Traffic congestion is a prevalent characteristic in urban areas. It leads to increased travel time uncertainty, air pollution, and high cost in transportation and health care for traffic accidents and other safety concerns [14] and [3]. With the advanced sensing, computing, and communication technologies, traffic management and operation can be optimized to mitigate traffic congestion while making efficient and safer use of the limited capacities of urban transport networks. Accurate traffic congestion prediction is one of the fundamental components of traffic operation because the information could be used to help adaptive traffic control to anticipate the upcoming congestion. The output and related information from the data are obtained and managed utilizing data preprocessing, encoding, feature engineering, and segmentation, and utilized as the input for deep learning or conventional machine learning for congestion prediction [15]. In machine learning for traffic congestion prediction and control, if the data collection and processing is not accurate and reliable, we cannot expect efficient or even optimal and reliable outputs and predictions. Data collection and processing, therefore, is an essential ingredient for the ultimate and successful completion of the project pertaining to autonomous vehicle traffic congestion prediction and mitigation. In this section we briefly review the existing approaches associated with the data collection and processing for traffic congestion prediction.

3.1. Sensors and Data Sources in Autonomous Vehicles

Detecting congestion techniques using roadside traffic sensors are sometimes inconvenient, time-consuming, or much more expensive due to maintenance cost. In some specific cases, the sensors are strictly confined to a communication protocol. Most of all, the covered area may be limited, and hence, the monitoring window should always be set in the middle of the network. Moreover, the collected traffic data are extraordinary large but are not comprehensive enough to accurately estimate and predict traffic states as they seldom consider the congestion effects finally. In traffic surveys for building congestion predicting models, the attributes mainly capture the impact of road traffic congestion which are often accident factors and road closures. To explicitly predict real congestion, the machine learning and algorithms supporting big data techniques are still scarce. In this study the forecasting algorithm has to be of low complexity and provide reasonable performance to become practicable for real road networks. First attempt shows that using the upstream information in the weighted negative likelihood Committee machine approach for global traffic state prediction achieves 56.5% percentage error in a noise-free environment. Grubinger and Ossen find that adaptive filtering methods reduce the error in case of congestion and assignment error by considering filtered upstream speed for predicting states of cellular automaton cells. Also, horse-race algorithms utilizing feedforward neural networks to predict traffic speed in urban environments are proposed, and the sequential nonlinear learning algorithm (SNLA) obtains the best results in terms of accuracy and learning time.

Various systems and sensors have been used for collecting traffic information and conventional Intelligent Transportation Systems (ITSs) [16]. However, the collected traffic data are limited and not comprehensive enough to accurately estimate and predict traffic states and hence it is necessary to integrate data and artificial intelligence techniques for this purpose. Moreover, congestion is mainly considered to be caused by accident, incidents or events in most studies [17]. For example, in the "Traffic Congestion Classification by Visual Features and Deep Learning Approaches" study, the research on traffic jams with Visual Analytics (VA) technology and deep learning architectures which both focuses on traffic events as congestion factors and handles different spatio-temporal transportation datasets.

Maha et al. [18] greatly but not solely aim (1) at enhancing the visibility of roadside operations by applying a vision based system for autonomous acquisition of roadside traffic photos. And also, Pélissier et al. propose a Smart Traffic Management Platform enhancing Visibility through Deep Learning (STMP-V) that addresses some unresolved research challenges and aims at improving the visibility of traffic operations.

3.2. Challenges in Data Collection and Processing

These cars can automatically supply some real-time traffic information to the centralized machine learning system, with no need to pave the way or close the streets and/or the intersections. An intelligent traffic surveillance system using an improved wireless sensor network framework for supporting intelligent transportation systems is proposed in. Additionally, constructing surrogate data has become an effective strategy to separate the task of data generation from model tuning. Examples of surrogate data include the 55,635 datasets of the US traffic that are provided by the US Department of Transportation (U.S. DOT) and its partners, as well as the semi-static route information provided by the French traffic monitoring provider TomTom. Using smartphone applications to create the training set can form another solution for future use, provided that the drivers' demographic can be counted in.

A fundamental necessity in developing a congestion management system using machine learning techniques is having a real-time dataset [19]. However, collecting such data is challenging and costly. Over the years, several methods have been adopted to collect traffic and congestion datasets. In the Class-Based Traffic Data-collecting Method and Segmented Zone division, footage captured from a surveillance camera is used to perform data collection and training. In-station methods have also been employed to perform simulation experiments and test the proposed algorithms. Furthermore, the collection process takes a lot of time, a large number of people (researchers or corresponding teams in the field), and significant resources. In this regard, autonomous cars equipped with some wireless communication facilities could be a good solution to help data collection for predicting traffic congestion in the future [18].

4. Machine Learning Models for Traffic Congestion Prediction

To achieve real-time traffic status prediction, we can associate the performance of the traffic management systems with responsibility of public administration to optimize the traffic status in large scale. Traffic prediction can be carried out from the analysis of historic data about traffic congestion in a certain period. Traffic managers correct a lot of variables—that change the traffic congestion—for traffic refreshments in sensor-based control; the sindetic outcomes of their operative actions can be studied to traffic forecasting. When a car runs in a territory, it captures the data around itself, so the vehicle system models themselves by knowing the velocity values of the road segments hit by the car. A reliable vehicle system median-prototype overlaps a great percentage of traffic instances of a distinct vehicle, imitation that the latter is a representative of its reference vehicle system median-prototype.

Traffic congestion is a common urban operational and environmental problem that affects human life and the economy. The primary solutions to prevent traffic accidents and reduce congestion must involve quantitative predictions of traffic flow states and early-warning traffic monitoring [20], which will help improve road network reliability. The main problem in public transport management lies in optimizing the timetable, the route assignment, and headways in order to minimize passenger traveling times and to satisfy their comfort and service-quality requirements. To solve this problem, we need to accurately predict the passenger flow demand for each bus stop and the passenger travel patterns for the whole-day period [14]. With the rapid development of technology such as the internet of things (IoT), big data, and cloud computing, researchers are now able to design more comprehensive, intelligent, and adaptive models that can further improve the precision of passenger flow prediction [21].

4.1. Supervised Learning Models

Traditional methods [8] (e.g., autoregression integrated moving average, back-propagation neural networks, and long-short term memory) are extended by leveraging high-dimensional spatio-temporal features with traffic flow and incident data. One of the unique features and contributions of the study is: for the first time, we incorporate spatial and temporal correlations in traffic flow data, satellite-based weather data, and incident information to predict travel time ensembles on multiple origins and destinations nodes at a large urban network. Moreover, we provide insights to discriminate deterministic and stochastic traffic modelling approaches at microscopic scale, i.e., establishing a causal relationship to predict the travel time taking advantage of traffic flow pattern in a first-hand way. We present a case study in Northern Virginia, US, we find our spatio-temporal model can significantly outperform conventional traffic prediction approaches, when compared against five years of probe-based Transportation Performance Measurement System (TPMS) travel time data obtained from VDOT, especially at less congested urban areas, which have less available probes and are difficult to capture with traditional methods.

An increasingly popular approach to traffic prediction is the use of machine learning. At the foundational level, machine learning-based prediction establishes a relation between input and output using a learning algorithm. The principle of machine learning-based traffic prediction is to investigate and learn the relationship between a variety of complex factors of traffic, as well as a large volume of historical data and predicted data. The fundamental features of machine learning-based traffic prediction methods can be seen as having the following characteristics: (1) using a large volume of historical data for learning rather than human expertise; (2) good adaptability and generality (avoiding trouble setting up traditional traffic flow models); and (3) high fault-tolerant, robust, and good practical capability of processing incomplete traffic data, etc. Therefore, based on these characteristics of machine learning, many scholars have applied them to traffic flow prediction [5], travel time prediction [22], and other aspects of traffic prediction.

4.2. Unsupervised Learning Models

In recent years, artificial intelligence and control algorithms have played a critical role in controlling urban mobility research, particularly for understanding traffic flow of self-driving vehicles, and other autonomous vehicles. In recent years, certain studies have focused on modeling the coordination between autonomous vehicles and red light phase switching mechanisms at urban intersections. The objective is to examine constraints associated with real-time heavy traffic impacts and switching control errors. Specifically, the ability to limit intersection throughput to accommodate the maximum backlogs through a preemptive control algorithm and the traditional phase-time coordination plan for vehicular flow have been tested [23].

Road traffic congestion forecasting techniques forecast future traffic flow in near-real time, serving a dual purpose of identifying traffic anomalies and allowing sufficient time for situations to be managed proactively. However, traditional time series models, often fitted for conventional time series forecasting applications, rely on the assumption of serious causality, whereas human-in-the-loop traffic flow is often a spatiotemporal data generation process. Therefore, these models become invalid for forecasting traffic flow under the time scales required for intelligent traffic management. Modern machine learning models, especially deep models, exhibit better capabilities, in terms of generalization, in identifying highly non-linear spatio-temporal causality by training on large amounts of data [9].

5. Evaluation Metrics for Traffic Congestion Prediction Models

[10] [24] The performance of models for predicting traffic congestion in real-world scenarios should be evaluated to ensure a balance of generalization capabilities, complexities, and favorability to the problem scenarios. For frameworks that integrate traffic state prediction as components, evaluation metrics deal with the correctness of road traffic data collection. Traffic prediction system models and techniques are rigorously evaluated with large-scale, multidimensional, and heterogeneous traffic data covering incident-induced congestions, recurrent congestions, and so forth. The significance of evaluating the prediction system performance lies in the operational disutility of predictive inaccuracies insofar as learned models are employed in making management and control decisions in real time.[25] A number of metrics were proposed to evaluate the prediction model in the literature, including R^2, Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), F1-score, True Positive Rate (TPR), and Variance Score. Traffic Light Control Reinforcement Learning Algorithm and Simulation were based on Reinforcement Learning (RL) algorithms and techniques, which are suitable when the problem can be modeled as a Markov Decision Process. For traffic signal control, the environment receives actions while it can return states and rewards. The Deep Traffic Light Control Strategy employed an improved deep deterministic policy gradient for DTS. Finally, although necessary, evaluation metrics are not a one-size-fit-all. Whether the prediction model is for predictive control, dynamic traffic assignment, or advanced traveler information systems, a trained model needs to achieve a satisfactory level of fitness to detected data. Therefore, closeness of means and variances of prediction errors over different conditions (e.g. traffic patterns, travel time) are typically crucial.

5.1. Accuracy, Precision, Recall, and F1 Score

[26] Uncertainty in transportation forecasts is an important source of risk to decision-makers, who rely on these forecasts to make decisions around transport networks. Addressing uncertainty in transportation forecasts can make them more actionable. Moreover, providing confidence levels alongside the forecasts naturally replaces the traditional ad hoc processes that convert point predictions into actionable decisions. This is especially true for transportation management decisions and learning systems serving them. Traffic management centres often use real-time forecasts, for example to provide recommendations to operators on signal timing or ramp metering [27]. Mathematical models of uncertainty help the operators to assess their confidence in these recommendations and thus make decisions. They may decide to ignore a prediction if it is not deemed confident, or to experiment by deploying recommendations but being ready to revert to regular operational procedures if needed, or to explore other possible decisions.[11] Traffic congestion is a significant issue for many cities around the world. It not only worsens the quality of life for citizens, and results in huge economic loss, but also worsens environmental problems like air pollution and greenhouse gas emissions. So, predicting traffic congestion and controlling it is of great significance. Traffic congestion predictions play a critical part in advanced traffic management systems. A range of machine learning techniques such as support vector machines, neural networks, fuzzy systems, and/or decision trees have all been applied to the task with promising results. With machine learning, as with any forecasting system, it is important to appropriately measure performance using established metrics such as accuracy, precision, recall, etc.. Such an approach to evaluation is informative, and the methods of assessing forecasters developed here should be developed more broadly for all forecasting systems in the context of traffic management and decision-support systems.

6. Real-Time Traffic Congestion Prediction Systems

[28]In this paper, we predict future traffic accidents that could occur in the user's driving environment by integrating several real-time road condition factors, including traffic flow amount, road occupancy rates, traffic speed, road weather conditions, and air pollution. A large-scale real-world traffic-variance dataset is used to train and verify machine learning models many times. The Hybrid Model Tree, Support Vector Machine, and Relevance Vector Machine perform better and fit the real-time driving conditions better. The driver is alerted when they approach a location at high risk of an accident, and near re-routing and parking space advice is given.

[29] [30]A traffic congestion prediction problem is solved by using a hybrid machine learning and internet of things (IoT) based predictive model. The IoT layer draws a multirelational graph from the existing traffic networks provides the real-time dataset to set a ground truth. Using the dynamic data and historical data stored in graph nodes, different machine learning models are applied to predict the road traffic condition at different parts of the city. The simulation results show that decision trees and neural networks have better forecasting performance. the combined usage of IoT and machine learning decrease the prediction error rate from 5.43 to 3.95% and increase the prediction accuracy from 94.57 to 96.05%.

6.1. Integration of Machine Learning Models in Autonomous Vehicles

It is necessary to mitigate the traffic congestion on the road. In the workshop of the Intelligent Vehicles Symposium in 2017, a challenge on the PASSAT field was given to the public via the AI driving Olympics to develop control strategies for traffic lights to manage the congestion for a pre-specified set of vehicles in the testing phase [16]. The challenge consists of a network of signalized intersections where all vehicle positions and velocities are controlled by a simulator. The objective of the competition was testing the generalizability of control methods in scenarios with unforeseen starting congestion.

Traffic is a dynamic system; forecasting traffic may be challenging due to the dynamic nature of the traffic network. Out-of-date traffic state estimations and low positional accuracy are also typical in traditional prediction methods [7]. Traditional traffic forecasting models usually fail to capture the small-scale variability and representations of human behavior uncertainty, because human behavior is quite different for different traffic participants, and even the same traffic participant can make different behavior decisions in different time contexts. Deep learning methods have illustrated excellent results for traffic prediction considering both aggregate traffic and individual vehicles [23]. Recent studies attempt to integrate deep learning methods with physical-first-principle models to capitalize on the advantages of both, and solving some problems of both methodologies.

7. Mitigation Strategies for Traffic Congestion

[31] It has been mentioned in the past that autonomous systems have an inclination to create traffic congestion due to the speed and comfort trade-off. This section will elaborate in detail upon potential traffic congestion mitigation strategies that can be implemented to remedy the

automatic manipulation of the vehicle speeds, so that traffic situations can be improved in many ways and then also volume necessarily affected. The core of the optimal control step of an effective mitigation strategy is disturbance modeling, traffic congestion prediction, and multi-vehicle traffic flow speed of motor without spraying detrimental factors of a greedy driver behavior that can enhance vehicle energy-max vocal consumption of running. Also, predict front and rear vehicles position. A local area velocity convection mechanism and a traffic information protocol work together to guarantee the position control precision and reduce unnecessary communication traffic congestion. Though one main source of vehicular traffic flow authority local or high-level feedback off congestion is the local area velocity term advantages are excellent of antithesis, decentralization, UDP/IP low team and cons, and bidirectional communication freedom.[32] More often than not, internet of vehicles (IoV)-enabled vehicles get stuck in traffic jams, considering the highly susceptible real-time vehicular mobility patterns. Thus, it is observed that the frustration that is caused by traffic jams can be abated by advance planning-based congestion detection and controlling mechanisms through proactive feedback approaches like data-centric routing and congestion-aware congestion protocols. The vehicular traffic congestion problem is especially predominant in vehicles and hence, various methods are proposed to address the issue namely: simulation-based clustering of GPS traffic data clustering and congestion detection, vehicular congestion awareness, a hybrid congestion detection protocol, routing algorithm for low impacting commuting, and A Link Stability Model.[3] Ramp metering is a proven, cost-effective strategy for traffic congestion mitigation. The capacity of a freeway with geometric or kinetic wave bottlenecks can be improved by regulating the number of vehicles entering the bottleneck at critical times. In this work, a reinforcement learning-based virtual ramp metering (VRM) approach was developed to control the flow rate at a virtual downstream location; thus, the numerically solved feedback control law is used. Importantly, the developed VRM application offers valuable insights; it can be seen that adjusting the perturbation element in the reinforcement learning can successfully separate the throughput maximization objective of the proportional-integral feedback controller from the hysteresis-minimizing policy.

7.1. Dynamic Route Planning and Traffic Signal Optimization

Most feature network-simplex traffic management models considering route flow are proposed to use the vehicle arrival detected by vehicle detectors and global position control system in the road network with a weighted sum combination of a congestion and queue length delay to predict the congestion rate of the whole road network. The vehicle detectors are presented by the road-based defined role on the number of vehicles in the neighboring detector area where a periodic signal control present an accurate and effective means however, the spatial resolution to which vehicle conditions can be synchronized with traffic light status is not considered at the intersection from all aspects. Hui et al. (2019) presented a queue-related traffic light optimization approach which capture intersection congestion of each movement (He et al., 2020). Traffic light controllers are able to monitor real-time traffic flow and represent the car flow that passed through each road using the exogenous variable (historic car flow).

Another multi-modal weighted frequent Phrase Sequence (FPSequence) mining and N-Bayesian-based probabilistic R-CNN models have been designed to predict the upcoming traffic congestion or accidents and consequent traffic diversion recommendation using GNSS GPS clustering algorithm to achieve efficient traffic flow under VANET. A network of smart cars will consist of V2I and V2V communication as an ad-hoc network while considering optimum traffic light control with the help of Back Propagation (BP) trained Multi-Layer Perception (MLP). Besides the system also supports coordination from conditional to unconditional events and can control all traffic junction with or without the pilot vehicle by also providing the top vehicle of the current system to have the flexibility of multiple control modes.

[33] One of the V2I interfaces can be a system that can evaluate trajectories based on predictions of an upcoming signal phase and interact with the system, e.g. via a compatible route planner. For instance, the authors of (Stogios et al., 2020) addressed a dynamic aspect of traffic light control by allowing vehicles at the front of the queue to share their predicted arrival time with the traffic light controller. The authors measured the superior performance in vehicle journey times and increased waiting times for road users stopped at the lights. Vo and Lee (2018) proposed an adaptive control Optimized Adaptive Traffic Signal System (OATSS) using dynamic traffic state prediction and trajectory-based optimization. The proposed system also aggregates continuously updated vehicle GPS data from smartphone applications, weather station, the traffic camera, and the vehicle data resources into feature vectors before inputting them to the constructed R-CNN model. From the skyline results, the most critical predictors are selected and fed into the K-Nearest Neighbors (KNN) models to

predict the stop—start probabilities. Along with the prediction module, a priority-based optimization problem is developed for construc-ting the optimal traffic signal plan by considering several decision metrics such as weighted delay, Harmonized Level of Service each approach, Safety index of modeled Lane width, and the sum of carbon dioxide (CO2) emissions. The effect of the traffic signal system on driver behavior is also analyzed. IoT based Adaptive Traffic Management System (AITMS) (Sambath et al., 2021) was designed using Raspberry Pi, SVM, and IoMT to improve the present traffic congestion system. The primary goal is to reduce the congestion of traffic in a smart city system and to provide a safe and advance traffic system.

8. Case Studies and Applications

[12] In this section/article, an overview of real-life applications is presented with respect to the use of machine learning approaches in the mitigation and prevention of congestion conditions within the transportation network. These applications were selected and presented as they involve the use of different machine learning techniques to solve transportation-related tasks in an attempt to provide a generic analysis that can be helpful for a wider audience seeking information on the subject. At the same time, a more detailed view of the real-life application is presented to provide a high-level view of a complete system. Mitigation of congestion and its prevention within the transportation network can be performed online using real-time identification of relevant congested sections and using prediction models.[5] Traffic congestion prediction systems could drastically reduce the impact of an unplanned event and help administrators manage traffic by predicting future congestion accurately. Among all potential applications involving machine learning and intelligent vehicles, congestion prediction could have one of the highest overall benefits. It was shown that one can predict the most important operational aspects of traffic flow in an urban area and accurately detect short-term traffic congestion using machine learning techniques. Such advances could be implemented through traffic forecasting systems and information displays that could guarantee efficient mobility in urban areas and on highways. By considering advanced models of driver behaviours and different vehicle trajectories, one can also predict the variation of density within the system. The developed algorithms are tested and validated using case studies for one of Lisbon's most critical and complex traffic sites, which is the Sete Rios huge roundabout.

8.1. Successful Implementations of Traffic Congestion Prediction Systems

Traffic congestion seriously depletes the performance of urban roads, with issues such as high emissions, loss of life, and increased travel time causing economic and operational problems. Urban planners utilize a traffic signal timing approach based on historical traffic light patterns, and the traffic flow and delay of each signal are calculated by models such as the Webster, the Greenberg, and the Van Haperen method [20]. Cooperative Urban Traffic Management (CUTM), will contribute to solving city-wide traffic congestion using an AI prediction model. C-4 indicates the average CO2 emissions in 10 min, C-3 is the emissions in runPt + 5 time slices, C-2 is the emissions in runPt + 10 time slices, and C-1 is the CO2 emissions in the specific time slice closest to runPt + 15. The sensors will acquire different traffic data such as urban lifeline health sensors and competitive learning sensors. The inputs of the algorithm are rainfall, temperature, air quality index, and dew point temperature, and the target of the method are the prediction of the daily data stream. Signal optimization can cause widespread high energy-efficient traffic travel. Signal consultation technology can timely collect nearby transport active information. Cutomize timing solution only serves currently book transport active according to advanced reservation request.The recent traffic state decision in algorithm collects definite factors of the active mode of transport. Daily travel demand changes for each active mode of transport. Based on the traveled questionnaire topics on actively transport organic and the patterns of an urban transportation circulation, transport observations may receive to influence the effective path and however handle vehicle signals, specifically. Moreover, these final rules decision system can offer only efficiently accommodation system and developed large-scale transport fires .

'Urban mobility has significantly altered by the increasing number of vehicles and traffic congestion. Machine learning (ML) methods have been utilized to predict traffic congestion and allocate real-time resources more efficiently [34]. DL has become popular in recent years due to its significant advantages, including its capability of handling big data, and high prediction accuracy. Urban planners are always searching for a reliable short-term forecasting method to optimize the traffic detection with their knowledge of off-line traffic data. Various state of the art sensors are used in the ITS system to predict near real-time traffic flow pattern [35]. Also, the collected data range from past traffic flow and weather forecast value to traffic flow in the immediate future. In recent years, several advanced feature extraction algorithms have been implemented for traffic state prediction problems. Most of these models such as empirical mode decomposition (EMD), ensemble empirical mode decomposition (EEMD), and complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) are introduced to predict nonstationary and nonlinear short-term traffic flow and also based on concepts drawn from Taylor's theorem. A. Kus and Yusuf Sancar displayed that EMD improved the performance of innovative approaches to multimodal short-term traffic flow forecasting based on six different multivariable time series data .

9. Ethical and Social Implications of Autonomous Vehicles in Traffic Management

Taken alone, ethical decision-making respects the rules in force and takes into account the usually rather small risk of accidents, which are not predictable in an absolute sense. This allows us to consider that these parameters are part of autonomous decision-making, which, however, allows us to reduce the accident risk as much as possible. In our research for urban autonomous driving, we presented solutions that could be adapted to these two complementarities: allowing urban planning to be actioned on [36]. These two main parts of this work alone could be considered a complete system for the ethical choice of automated trajectory. We present in this paper two main components, trajectories generation and assessment, completed by a strict framework that ensures all the choices will be made using the same ethical policy.

Data we can exploit and actions we can undertake to ensure that the use of these technologies in the management of mixed traffic (including non-autonomous and autonomous vehicles) is ethically and socially responsible. The main focus of this paper is to summarize the debates and proposals made in order to solve these problems. To build better transportation systems and technologies all these challenges need to be addressed with an open and responsible discussion that involves engineers, computer scientists, ethicists, politicians, and common citizens [37]. The most important concern is the security of the entire transportation system. The goal in the development of existing theories and methodologies in planning and controlling transportation systems is to ensure that all transport users are safe. This is especially important in the case of mixed traffic, in which automated and non-automated vehicles co-exist. The behavior of road users who do not have control of their vehicles becomes in such cases an important, not fully predictable factor [38].

9.1. Privacy Concerns and Data Security

Instead, data provenance is about recording the history of all the actions performed on a dataset, which is important in the context of security. How reliable and secure is the data? Based on how the data is generated, recorded, and managed, various traceable provenance-as a-service blockchain scenarios could be analyzed, ensuring the data to be accurate and unbiased. Therefore, data provenance allows one to understand the data pipe- line, thus raising awareness of the socio-technical data processing settings while underpinning privacy and data security [39]. Moreover, the type of interactions is key to speeding up and scaling a security measure, as interactions co-determine identity and risk. Important is also the endpoint security of the data module, taking care of encryption and decryption of transported data.

The development of autonomous traffic of vehicles (AVs) typically relies on the collection and management of user data [40]. Data collection deals with privacy and data management concerns, which involve various regulatory strategies. There are legal frameworks like the EU's General Data Protection Regulation (GDPR) and China's Personal Information Protection Law (PIPL). Vehicle-to-everything (V2X) communication shapes vehicle operation, particularly with information channels and applications that use such data. This chapter discusses the general needs and challenges related to privacy and data security and even touches upon data provenance metrics.

10. Future Directions and Research Challenges

It is worth mentioning that datasets with different experiment settings (e.g., with and without traffic signs in the environment) and different AV repercussions (e.g., original and isolated experiments to observe the influences of specific functionalities) should be also considered. Moreover, the training and testing sets should include a diverse and balanced variation of traffic demand characteristics and mixed proportions of CVs and conventional vehicles. Rigorous follow-up verifications on public roadways will eventually be required to verify results in simulation via scale-free measures. Considering the cost of such field experiments, researchers should optimize the sampling rate, data storage, and analysis. Furthermore, at this stage, it is not necessary to conduct large-scale infrastructure updates as AVs are still in the prototype phase. A proposal for prospective machine learning models to predict AV-tracked traffic dynamics, such as speed, acceleration, and position with no response, is the natural next step. Regarding model design and parameterization, the optimum architecture of machine learning (ML) models and therefore the choice of the acceptable ML algorithms and hyperparameters might depend on the precise simulation environments and physical traffic models. Consequently, it would be helpful to assess the theoretical implications of different algorithmsÂ¿ choices in proportion to the situation.]

[41] [42] As the number of connected and intelligent vehicles increase, they may be able to collect and share data with relative ease. That is, autonomous vehicles might help in enhancing traffic conditions while leveraging machine learning technology. These vehicles are expected to navigate using high-precision maps and communicate with each other and infrastructure. Therefore, there is an urgent need in developing accurate traffic prediction models that can facilitate AV-driven data analytics and real-time decision making. In the optimized scenario, analytical tools would be capable of predicting traffic conditions ahead of time using data shared between connected vehicles (CVs) alongside with the static and real-time traffic information. Then, the intelligent vehicles will react according to the shared knowledge in such a way to enhance the overall traffic flow. This section suggests that future studies could prioritize instantaneous traffic prediction by collecting data off stationary traffic signals. As the AV technologies evolve, the current massive traffic signal infrastructure can be effectively utilized for traffic flow prediction. In particular, real-time traffic information could be merged with historical static traffic information, both of which can be further complemented with transient and historical traffic data shared among connected vehicles.

10.1. Advancements in Deep Learning for Traffic Congestion Prediction

The mandatory speed prediction assists in mitigating the traffic congestion by commanding the traffic signal control. Its spatio-temporal characters, such as motherboard contribution speeds, neighboring roads contribution speeds, road segment speeds, and the speed spatial relationships between all those characters, can be comprehensively learned. Meanwhile, with the global road structure information, i.e., topological adjacency relationship between road segments, synchronized historical speeds, instantaneous speed, and local region road network environmental factors, such as elevation information, automatic feature extraction and propagation at multi-layer network levels, raw traffic sequence features can be further learned and then collectively cross-modally fused together. The first disadvantage of the wireless model can be alleviated seeing prototypes generated with statistics close to the median and raking in the middle 20% ranks out of the overall SEI-normalized relative rankings.

Conclusions are drawn and the authors mention several limitations and future perspectives. A novel deep learning cross-attention and fusion-based traffic speed prediction framework is therefore designed, that is called the TRACER system.

[43] As one of the most serious transportation challenges, urban traffic congestion has a significant impact on the environment, economy, and the quality of life. Predicting and managing traffic congestion, as a way to mitigate traffic congestion, is crucial for making informed decisions about routes, expanding road networks, and improving public transport system, among many others. Due to the accuracy of traffic congestion prediction and the robustness of traffic models, lots of Machine Learning (ML) techniques, including Artificial Neural Networks (ANNs), have been used in traffic flow prediction and traffic congestion detection. However, the ANNs such as the vanilla RNN or LSTM can only 'see' past historical speeds and predict future speeds. In other words, the heterogeneity of traffic data sets is neglected. We can see that both the spatio-temporal characters of urban traffic are essential for accurate traffic congestion prediction. Therefore, the spatio-temporal traffic congestion prediction problem in this paper is converted to a spatio-temporal traffic flow prediction based traffic congestion prediction problem.

Reference:

1. Tatineni, S., and A. Katari. "Advanced AI-Driven Techniques for Integrating DevOps and MLOps: Enhancing Continuous Integration, Deployment, and Monitoring in Machine Learning Projects". *Journal of Science & Technology*, vol. 2, no. 2, July 2021, pp. 68-98, https://thesciencebrigade.com/jst/article/view/243.
2. Prabhod, Kummaragunta Joel. "Advanced Techniques in Reinforcement Learning and Deep Learning for Autonomous Vehicle Navigation: Integrating Large Language Models for Real-Time Decision Making." *Journal of AI-Assisted Scientific Discovery* 3.1 (2023): 1-20.
3. Tatineni, Sumanth, and Sandeep Chinamanagonda. "Leveraging Artificial Intelligence for Predictive Analytics in DevOps: Enhancing Continuous Integration and Continuous Deployment Pipelines for Optimal Performance". Journal of Artificial Intelligence Research and Applications, vol. 1, no. 1, Feb. 2021, pp. 103-38, https://aimlstudies.co.uk/index.php/jaira/article/view/104.