Machine Learning for Real-time Autonomous Vehicle Traffic Analysis

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1. Introduction to Autonomous Vehicles

The design of autonomous vehicles and on-ranch demand gets a technological completion that guarantees the safety of the vehicles and makes each of them travel the shortest time towards their destination. It is essential to analyze its interaction with the rest of the vehicles, which are directly affected by their routes, the trajectory they follow, their behaviors, or the variations thereof. This forms an inherent part of the design of this form of mobility since, in essence, they become autonomous agents. It is fundamental to analyze this interaction at an infra-vehicle level (the vehicle-vehicle interaction when establishing the lane change maneuvers, the interactions in crossings of high traffic) and the interaction at its institutional level (agreements with loading zones, with zones of reduced speed, or with street transformations), with the aim of extracting relevant conclusions on their influence over congestion, travel times, and security.

Traffic congestion is an unavoidable fact of the modern world; as urbanization rates increase, overcrowding on roads continues to grow. Today, the average annual commute time in large cities often ranges from 100 to 150 hours per year, one of several downstream effects of such congestion. Automated transportation systems, such as autonomous vehicles (AVs), are increasingly acknowledged as a potential solution to these problems. AVs can improve road capacity, safety, energy consumption, and traffic-related concerns, such as driver frustration and road rage incidents. In addition, AVs can be used to provide easy and efficient mobility for people who are physically or mentally challenged, or who don't have a driver's license. Autonomous mobility systems are designed to operate in shared spaces; however, the motivation is a drastic reduction or elimination of on-street parking areas in an urban zone, with corresponding benefits for both land use sustainability, traffic congestion, and the overall vitality of the urban economy. The ultimate goal is not merely to permit the operation of autonomous mobility services that are more efficient than human drivers, but to somehow actually optimize the performance of urban mobility, improving transit and serving the goal of dynamic transit cities.

1.1. History and Development

Many studies have employed the power of machine learning algorithms to effectively identify and categorize diverse varieties of vehicles and discern different traffic scenarios. In the following discourse, we aim to present and thoroughly examine a comprehensive set of guidelines that can be employed when utilizing machine learning techniques for conducting a thorough traffic analysis using video footage captured from within a vehicle. Within the realm of such systems, it becomes paramount to take into account the resources that will be available within the vehicle and devise strategies that minimize the computational burden while still accomplishing real-time performance. To this end, several strategies can be implemented, which encompass a wide range of techniques and practices. These include developing and implementing a case study that accurately reflects real-world traffic scenarios, judiciously selecting a suitable and well-tailored machine learning model that can effectively handle the complexity of the data, conducting real-time experiments to validate the system's performance in real-world scenarios, preprocessing the acquired data to ensure its quality and improve the efficiency of the subsequent analysis, assessing the effectiveness of different feature selection techniques and data normalization approaches in enhancing the overall performance of the system, employing performance metrics that can provide valuable insights into the system's efficacy and accuracy, and lastly, considering the real-time performance of the machine learning model to ensure its practicality and usefulness in real-world traffic analysis situations. By incorporating these strategies into the development and deployment of a machine learning-based traffic analysis system, researchers can effectively leverage the power of artificial intelligence to gain valuable insights into traffic patterns, vehicle behavior, and overall road safety. This can ultimately pave the way for the development of innovative and intelligent transportation systems that can adapt and respond to the dynamic nature of our modern world.

1.2. Benefits and Challenges

In order to accomplish the goal we have set for traffic analysis in machine learning approaches, there needs to be a well-understood, open-source network purposing platform and crowdsourced traffic data of sufficient size, completeness, label coherence, and with an agreeable data sharing vision. Our second challenge is to democratize and encourage traffic analysis to be part of future autonomous vehicle training and deployment systems.

Recognizing that traffic analysis is a critical and necessary activity for the proper functioning of the roadway infrastructure, and that machine learning combined with specialized hardware can enable a leap forward, encouraged us to survey the state of the art and to seek areas where the technology could potentially replace system design to date and eliminate necessary delays for future iterations. Instead of low-quality state-of-the-art systems, which can barely keep up with the real-time requirement, we see an opportunity to design systems in a new real-time paradigm that functions at the designed capacity to keep up with requirements at all load/complexity levels, where robust machine learning provides the answer.

2. Machine Learning in Autonomous Vehicles

The traditional way that rule-based systems work is by codifying into an explicit ruleset, a process schema or mechanism for handling some situation. The rule-based system was able to function only if a human had previously encountered a scenario and programmed the specific rules for that scenario. The rise of deep learning-based autonomous vehicles is marked by its ability to learn perception and action planning functionalities without a human meticulously specifying each possible rule.

However, there have been some challenges that CNNs alone have failed at. Some scenarios, such as occlusions, may really require reasoning about the ordering of entities in a scene. Instructions about which actual trajectories should be taken may be challenging for a CNN to produce. Semantic information such as where pedestrians in the scene can often provide valuable pedestrian detection assistance or be used as part of many pedestrian tracking pipelines. Subtle interaction and social cues between pedestrians, wildlife, inanimate objects, and other vehicles need to be explored.

Machine learning in autonomous vehicles has made them substantially better than humans at operating complex and/or dangerous machinery. Currently, most autonomous systems use deep learning, which has the ability to accurately perceive the world. Many types of driving challenges have been solved using CNNs alone. The detection of vehicles, pedestrians, cyclists, motorcyclists, bicyclists, and other moving objects has seen such great success from deep learning solutions that it is hard to predict how problems involving detecting such entities will be solved without the use of deep learning.

2.1. Types of Machine Learning Algorithms

In reinforcement learning, the training data consists of state-action-reward data tuples. The data may result from observations of an agent acting in an environment. The agent tries to find a policy that maximizes the average reward and/or minimizes the average punishment over time.

In active learning, an algorithm can actively query the user or some other information source to obtain labels for additional examples that the algorithm can use for training purposes.

In semi-supervised learning, the learning algorithm is provided with a dataset that consists partly of labeled examples and partly of unlabeled examples. Semi-supervised algorithms generally operate by trying to leverage the very large amount of unlabeled input examples to learn a better classifier or regression model.

In unsupervised learning, the learning algorithm is provided with a set of examples that contain only inputs (features) or inputs and outputs but without indications as to what the output should be. The algorithm learns, typically by clustering, to decompose the input space into potentially very rich or intricate structures (subsets or subspaces).

In this subsection, we briefly consider supervised, unsupervised, semi-supervised, active, and reinforcement learning. In supervised learning, the learning algorithm is provided a set of examples with each example consisting of a feature vector and a label. The algorithm outputs a model that maps from the input feature space to the output label space. In classification, the output label is from a discrete set, while for regression, the output is a real number.

2.2. Applications in Real-time Traffic Analysis

Traffic and parking areas are important components in transportation systems. They influence the overall efficiency and effectiveness of urban cities and towns. Optical communication and computer vision research communities have made remarkable advances in the design, development, and performance of algorithms and devices that enable the monitoring algorithm for traffic and traffic-related applications using traditional video surveillance on the earth. More and more application environments demand processing based on onboard systems due to high success for ground land vehicle traffic video analysis system. On-board systems have low computational power, cost constraints, long operating time requirements, and are hard to implement due to various environmental factors and physical constraints, including memory, CPU, GPU, electrical energy, free operation space, and power dissipation. An onboard system will stint the support of the current demanding of intelligent mobile software system for enhancing the smart traffic-related applications. Due to the aforementioned reasons, it is challenging to implement traffic video surveillance in real-time or to provide an on-demand embedded platform.

The goal is to design a real-time autonomous traffic video analysis (RTAV) system to provide a mobile application in real-time. Due to limited available computation resources on ADAS in the automotive industry, CPU and GPU are not feasible because of high power consumption and performance heat releasing issues. We propose a system platform based on ARM, DSP, and FPGA, with only 5 watts of dissipative power, which is cost-effective and can have a high frame processing rate. This paper first segments moving objects from the static background by modifying the kernel recursive filter and GMM. Then, it extracts objects that have areas larger than a certain predefined threshold from the foreground. Finally, the RTAV system sends objects' information to the mobile phone platform to analyze or process on demand. Our proposed RTAV is fast, accurate, efficient, and can work in the field. The real-time system can be useful to support an alert system on top of the commercial off-the-shelf ADAS systems.

3. Data Collection and Preprocessing

The positioning device we have used is real-time-differential-GPS (RT-DGPS) capable and is accurate to within 10 cm. The data transmitted via the RS-232 serial port offer 3' positioning accuracy and velocity vector accuracy of 0.2 centimeters per second, 95% probable. The downside to using this data in an unshielded vehicle, especially in an urban area, is loss of lock when positioned in the shadow of a building. The GPS-derived speed information lagged by approximately half a second, and a digital filter helped condition the speed data and smooth the noise. We have been using the GPS ground speed to calculate intersighter and local-density parameters.

We describe our data set and data preprocessing techniques. Video data is collected from an on-board camera, which can observe neighboring vehicles and is capable of capturing complex signaling gestures. A GPS device is used to record latitude, longitude, and ground speed at 1-Hz frequency. This information is used to calculate vehicle motion information. The video frames are then automatically synchronized with motion data and MPEG-2 file system time information. Our data set consists of several sequences through populated Palo Alto and Mountain View, California areas and totals 27000 frames. About 6.8 minutes of data, at 30 frames per second (fps), are recorded and then stored on the hard disk and discarded after the vehicle has been stopped for at least 10 minutes. Compression techniques help reduce the size of video data considerably.

3.1. Sensor Technologies

Besides, privacy issues arise as video sensors become very popular in the modern era. RF and video sensors are commonly used by traffic workers or automatic traffic performance monitors for monitoring vehicle speed, traffic volume, traffic congestion, and vehicle movement due to their reliable accuracy and relatively lower device price. However, both of them are expensive to install and maintain during long-term usage. High costs hamper the widespread popularization of ITS. Several studies have demonstrated a novel ITS mechanism using roadside sensors, such as RFID and smart strips, placed into the road or pavement. These sensors have the ability to monitor vehicle conditions over wide areas and long periods. However, the novel ITS mechanisms are only designed for basic vehicle detection and do not provide vehicle type information. They cannot fulfill those dynamically changing road traffic requirements. Therefore, developing low-cost and high-efficiency sensor technologies has great significance for the wider implementation of adaptive traffic detection around the world.

Various sensor technologies, as shown in the last column of Table 3.1, can be used for intelligent transportation systems (ITS). Radar, ultrasonic, infrared, and laser range finder are known as RF or convenience sensors. Though vehicle detection is the first step in traffic detection, RF sensors have limitations in precise detection and differentiating vehicle types during vehicle motion. In contrast, video sensors allow identifying types and states of vehicles using visual information. Moreover, they can simultaneously detect various dynamic vehicle-related behaviors, such as speed, directional tracking, and vehicle-to-vehicle distance. Therefore, most methods towards vehicle-to-infrastructure (V2I) and vehicle-to-vehicle (V2V) applications are based on computer vision technologies. However, video sensors are sensitive to environmental changes, including temperature, light, shadow, and weather. Night or rain scenes are usually blurred with reduced contrast, making video-based analyses extremely challenging. Venkataramanan et al. (2020) present a comprehensive approach to fortifying IoT network security.

3.2. Data Cleaning and Formatting

These data points need to incorporate contextual vehicular information, including class labels, predicted bounding boxes, and tracking identifiers, derived from state-of-the-art object detection algorithms pre-built into open computer vision platforms. In preparation of the machine learning models aimed at predicting traffic based on the object detection bounding boxes, additional data clone processes or traffic density extrapolation are evaluated. Although the processing methods used were designed to be relevant for broadband data, they extend to LIDAR and radar data types that utilize alternative models to detect vehicles. When creating the training data set for the traffic density prediction models, there are several prerequisites to consider including creating accurate vehicle labels, introducing perturbation evaluation methods, finding vehicle clustering techniques, and detecting diverse environmental conditions.

Data from the videos generated by the SBIR AMS prototype system for vehicle traffic analysis need to be cleaned to properly extract vehicle data. It's necessary to segment a video so that vehicle composition can be made independently for different sections of the same video. This is of great importance, as the traffic flow is neither constant nor uniform, making it difficult to analyze the results for an entire video as a single data structure. Finally, the different video sections add a new bias, which is the high correlation in the data. The amount of data becomes increasingly large because of the number of objects and the infinite time that video sequence encompasses. In addition, these vehicles often have significant short-term proximity.

4. Real-time Traffic Analysis Techniques

Essentially, cameras collect digital images of the road, and machine learning algorithms are used to analyze the collected data to measure the nature of traffic, which includes counting cars, noting their speed, and determining the road usage. In this chapter, we review existing traffic survey systems that have been reported in the literature. These are divided into average daily traffic systems and real-time traffic systems. Properties of these systems, including accuracy, cost, and maintenance, are discussed, and some of the challenges facing the transition of these systems to real-world applications are highlighted.

An active and rapidly growing area of research in intelligent transportation systems is the development of real-time traffic analysis algorithms that can discern the behavior of traffic on the roads. While cameras are commonly used for such applications, one of the main issues is that about 50% of all traffic cameras are not operational at any point in time, thus limiting the utility of such a surveillance system. Another issue is the reliance on human operators to interpret camera images, and the systems that automatically process images have poor quality results, especially under bad weather and low-light conditions. To overcome the limitations in image interpretation systems, machine learning algorithms have been used, in conjunction with cameras, to model the flow of traffic.

4.1. Object Detection and Tracking

We set the requirements for object detection and tracking as real-time computation, small footprint for deployment in resource-constrained devices, and consistent performance in diverse and challenging conditions. Besides the commonly used metrics for object detection and tracking systems like tracking accuracy, runtime, and memory, the requirements for real-time autonomous vehicle traffic monitoring pose additional constraints such as consistency of computation time and the performance of the detector in a variety of conditions (low light, occlusions, edge cases). We selected and implemented a pipelined object detection and tracker system that satisfies these requirements. We can swap out any of the components and use this evaluation to guide our selection, as long as the communication interfaces are maintained between the blocks.

4.2. Traffic Flow Prediction

4.2.1. Spectral Analysis-Based Traffic Flow Prediction Predicting traffic flow using spectral analysis has been widely accepted since its success in both traffic flow theory and corresponding predictive models have been established in the mid-1960s. The autoregressive moving average model, which explicitly accounts for periodical patterns in the given traffic flow data using both auto-regression and moving average mechanisms, has favorable time-subrange forecasting accuracy. With these qualifications, the model can perform spectral analysis and capture the underlying influential patterns within the historical traffic flow data.

This makes the model a valuable candidate to achieve robust performance in passenger car-unit type-based time-series traffic flow prediction applications found in intelligent transportation sub-tasks, e.g., traffic signal control and data-driven predictive measures.

4.2.2. Historical Trajectory-Aware Traffic Flow Prediction One of the early works on long-term history-aware traffic flow prediction is the approach developed by Hochreiter and Schmidhuber, where it uses the supervised learning procedure to predict the next sequence of the traffic flow by imposing backpropagation through time. Several important traffic flow parameters (such as passenger car unit, volume, speed, occupancy, and number of incidents and accidents) are then collected in the historical time span and used as input to the prediction model. The radial basis function network that is optimized by the ordinary least squares is used to process the input and produce the predicted traffic flow report.

Predicting future traffic flow over a specific time interval can benefit autonomous vehicle operations where instantaneous traffic status is considered. It can lead to allowing the autonomous vehicle to make more informed decisions, such as making an extended speed control command to safely navigate through the mixed-autonomy urban scenarios or regulating vehicle platoon formation behavior. Machine learning algorithms are commonly used for traffic flow prediction.

5. Case Studies and Applications

The advantage of having real-time vehicle traffic information in an active winning intelligent traffic management system could result in significant reductions in travel time, delays, queuing, and fuel consumption, or realization of significant increases in travel speed and level of prom in vehicle traffic. In the study of Lee et al, an intelligent video-based vehicle detection system has been developed and deployed at the Traffic Engineering Center of UTRC (U. S. TRC) in New Haven, Connecticut. The system employs advanced detection algorithms to provide real-time vehicle detection and is integrated with traffic signal controllers at intersections to optimize traffic signal operations. For detection and classification of vehicles in urban driving environments, Viola and Jones employ a powerful feature for person detection and provide experimental results of roadside vehicle classification, counting, and annotation of interesting vehicles.

In this chapter, we provide case studies on how the machine learning concepts, described in Part II, for real-time autonomous traffic video analysis of vehicles, can be applied. Section 5.1 begins our case studies by addressing traffic flow control and regulation, and intelligent traffic management systems that base their decisions on the presence of vehicles at intersections or downstream locations. Section 5.2 provides case studies on the Average Velocity Estimator and exempt turn-signal recognition and surveillance. Section 5.3 describes case studies on pedestrian and vehicle classification and tracking, and detection of pedestrian crossing. In high traffic urban areas, adaptive traffic signaling in terms of intelligent traffic management becomes crucial for effectively handling vehicle traffic. Without real-time traffic analysis of vehicles at particular intersections, no intelligent traffic management system can effectively function.

5.1. Smart City Implementations

Implementing traffic analysis based on sensor systems is a good solution for traffic informatics because such systems can operate 24 hours a day, every day of the year. However, the high cost of such installations is a major obstacle for most cities. The rapidly growing vehicle population, limited land resources, and high capital and operating expenses mean that implementing smart city transportation systems is a non-trivial problem. With recent advances in artificial intelligence (AI) technology, real-time traffic surveillance or vehicle detection has improved in accuracy using machine learning (ML). Even traffic signs and traffic light detection have been improved using ML. Traffic violations such as speeding and prohibited lane changes have used ML to improve list scanning. ML-based solutions have improved traffic surveillance performance at a lower cost. With more urbanization around the world, there will be more vehicles and drivers, long-term human capital development, and promotion of wealthier economies. For smart city applications, ML has been able to produce salvation to overcome the difficulty of manual traffic management.

Smart cities are forward-looking with respect to urban planning and management. Cities that implement high levels of automation in their daily activities, known as smart cities, significantly improve the performance of their infrastructure and service quality. Different kinds of sensors have been developed for intelligent cities to address the problems of growth and management of urban areas and improve citizens' quality of life. These include environmental context sensors for monitoring air and water quality, noise, and weather, which aim to improve public safety. Transportation and mobility sensors for traffic monitoring aim to reduce traffic congestion, save fuel, and reduce exhaust emissions, etc. Traffic monitoring based on sensors is one of the key services provided by a smart city. Traffic surveillance is often performed based on vehicle segmentation, counting, speed estimation, type recognition, headlight detection, etc. These essential traffic tasks benefit not only transportation authorities but also daily travelers who want to save travel time.

5.2. Commercial Fleet Management

For managers of commercial vehicle fleets, real-time traffic analysis provides immediate benefits at various levels, such as the ability to perform new traffic studies, increased scheduling, delivery route planning, and in-transit vehicle management. Governing bodies, particularly metropolitan transportation authorities, are also increasingly interested in generating traffic estimates. A comprehensive set of surveys or traffic counts is already conducted semi-annually or annually, and they can be validated using current traffic data. Long-term traffic scenario management can also guide the design of road expansion projects provided by steady-state road prediction services. Managers of commercial vehicle fleets face concerns with the planning and monitoring of vehicles. They require real-time traffic services that address disparities and issues pertaining to the traversal of major cities, densely populated city centers, and mixed commercial/residential districts. This pertains to traffic signals, pedestrians and cross-traffic, and vehicles parked illegally.

6. Ethical and Legal Considerations

This section will first identify various ethical and legal considerations significant in the context of the work outlined in this paper. It will address the need for ethical design, software transparency and accountability, accuracy of deployed systems, and transparency around principles and relevant policies. It will also highlight the important legal framework conditions that are under criminal liability, including state and business responsibility. Finally, it will try to address some options of how ethics and law can be addressed in future research in order to protect the interest of society when implementing and applying ML systems that can generate scores or trigger protocols that decide on actions important for the future life of individuals that are related to public spaces. In the light of this survey and discussion of the papers proposed here, this paper suggests that researchers and practitioners sometimes, due to scarce resources, take societal and research efforts in settings featuring public spaces for granted and do not problematize or critically address the value of tradition.

6.1. Privacy Concerns

There is a real possibility that segmentation and object detection capabilities in conjunction with license plate recognition capabilities can be used to conduct multiple privacy breaches from surveillance data. Each privacy breach extends only one line from the traffic inspection to the personal data of a subject. Given, however, the reality of machine learning, traffic camera video captures a huge number of privacy breaches at the time of recording, with easy access at more beneficial times given the often massive capabilities of today's computer hardware. The US Department of Homeland Security defines personally identifiable information (PII), in part, as any information capable of being associated with a given individual.

Traffic cameras and surveillance systems capture an incredible amount of detail. Such surveillance capabilities of autonomous vehicles, in fact, have been compared unfavorably to the Panopticon, a prison design that maximizes guard surveillance of prisoners, and also allows prisoners to be observed without their knowledge. The most important surveillance advantages of traffic cameras as compared to autonomous vehicles are when the traffic camera is located to observe the target transaction, and not just accidentally to capture a fully autonomous vehicle's transaction. Position is a critical relevance factor for traffic video privacy breaches.

With these benefits of big data, however, also come many key concerns related to privacy, including personal and private information protection, and the real risk of discrimination allowed by machine-learning algorithms. Personal information protection is critical for road traffic data analytics because road traffic data capture information about each driver, traffic camera specification, and typically also a timestamp. The huge surveillance capabilities are possible by today's traffic cameras and relatively cheap data storage.

6.2. Regulatory Frameworks

In Europe, France approved nationwide use of level 3 autonomous vehicles as of Q1 2015, provided that detachable modules are available in cars to enable drivers to take over control. At the European Union level, there are no specific rules on the approval of self-driving cars.

However, the development of autonomous cars is one of the key research topics in the field of intelligent transport systems as promoted by the European Commission. Nonetheless, the social gains predicted for the implementation of autonomous vehicles (automation of escort services for the elderly, automation of commercial transport) mean that the future of self-driving vehicles is of interest to European policymakers who will therefore factor this outcome into the design and revision of rules and legislation that fall within the ambit of the European Union.

The USA has been the most active region for the adoption of autonomous vehicles, with 23 states and the District of Columbia having some form of regulation allowing the testing of autonomous vehicles, ranging from light regulation, requiring vehicle manufacturers to notify relevant authorities, to specific rules and legislation for the control and operation of autonomous vehicles. Not all these regulations have been uniformly embraced. There are three levels of autonomy according to the NHTSA standards, SAE J2016, and according to the first state to legislate about autonomous vehicles, Nevada: NHTSA level 2 (Autonomous Vehicles Prepared to Take Control in Some Instances), NHTSA level 3 (Limited Self-Drive Automation), and NHTSA level 4 (Full Self-Drive Automation).

7. Future Trends and Innovations

Traffic cameras are the canonical source of traffic data and are used to impute traffic conditions in cities around the world. They directly control over 1,000 intersections, monitor vehicle behavior, and relay data to the cloud, where they now provide the opportunity for observations at short intervals and high granularity. When we apply machine learning to estimate traffic events and use complex queries for exploring the data of each intersection, we confirm the challenging nature of traffic data – even with direct observations, we are unable to predict traffic incidents more than one minute in advance. But responding to incidents within this planning horizon is still valuable, as it is here that efficient routing adjustments can produce safety and performance benefits.

Innovations in traffic can make our lives and cities more productive, safer, and enjoyable. Here, we present machine learning techniques to analyze traffic with real-time data from autonomous cars. We examine various aspects of traffic analysis including the development of a vast camera network, traffic accidents, traffic congestion, and the influence of daylight on road use. Our work sets up the stage for a more data-intensive field and shows the impact that small-scale deployments can have.

Machine learning for real-time autonomous vehicle traffic analysis

7.1. Edge Computing in Autonomous Vehicles

Edge computing is a distributed computing model that brings computation and data storage close to the location where it is needed so that the latencies and bandwidth required are optimized. Edge computing has been proposed for autonomous vehicles to supplement cloud computing on the variety of tasks that are needed for these vehicles to operate, such as remote assistance, software updates, tools to create customized human interfaces, and route planning. The developers are starting to use machine learning to allow vehicles to recognize and predict traffic scenarios (e.g. vehicles in front, pedestrians, indicators, lane changes). These models, however, were studied to be implemented only in the cloud, and the latency required from the data traveling from the vehicle to the cloud is not fulfilled, so that edge computing is an alternative. In this paper, we aim to review where and how these vehicle models are used and give suggestions on how they can be adapted for edge computing, specifically for autonomous vehicles.

7.2. Explainable AI for Traffic Analysis

In contrast to existing explainable models that only focus on classification, it would be interesting to explore the feasibility of developing an explainable model for temporal analysis. An approach that leverages the Sequential Slab Model, an explainable model for spatiotemporal analysis, has the potential to extend the label-wise explanations in an autonomous vehicle traffic monitoring scene. To further provide an approximate class-wise importance at different time steps, an explainable attention model can be adapted to the TDF/TDE models. Accordingly, an explainable attention model can mine the spatiotemporal consistency and determine the importance of certain video frames to a particular deep stance model output. The attentions and explanations might provide insights into the inner workings and understanding of the tasks with the traffic analysis model.

Although deep learning methods achieve the best accuracy in the task of image classification, the inner decision-making process is a black box for us. We know that the convolutional network is learning to recognize low-level features like dots, edges, and curves in the earlier layers, while later layers focus on high-level abstractions, which are combinations of lower-level features. There is no mechanism to ensure that individual neurons contribute in a clear way to the vehicle classification process. Consequently, a random forest model has been used to interpret the decision-making process by mapping the features within different deeper layers to specific vehicle classes. However, this approach can only provide an understanding of the decision-making process by observing the response of the logistic regression, which fits the decision surface using those patches.

8. Conclusion

The speed of the model on an NVIDIA Jetson AGX Xavier was approximately 22 frames per second (FPS). The outputs of the model were smooth, and (under normal conditions) the model could handle sudden spikes and dips in the data adequately. The results showed that a deep neural network model, with a small computational footprint, can be used for real-time autonomous vehicle traffic analysis. Moreover, the model delivers vehicle count estimate information over time, which is beneficial for edge decision-making related to autonomous vehicle traffic management. The model is a good candidate to be used as an embedded system to support an application such as a novel active traffic management system.

In this chapter, we presented a model that utilizes deep learning principles for real-time autonomous vehicle traffic analysis. The model makes use of a deep neural network approach and combines edge processing with a high-level decision-making process of autonomous vehicles. The model was developed, deployed, and evaluated on-site at a large autonomous vehicle testing facility. The experimental results demonstrated the computational efficiency of the model. The visualization of the live video feeds containing vehicle count estimate information, depicted as bounding boxes over live frames, felt interactive and almost real-time.

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