DEEP LEARNING SERVES TRAFFIC SAFETY ANALYSIS: A FORWARD-LOOKING REVIEW

## Abofazl Razi ∗†, Xiwen Chen†, Hao Wang,

School of Computing Clemson University

## Huayu Li

Department of Electrical and Computer Engineering University of Arizona

## Brendan Russo

Department of Civil Engineering Northern Arizona University

## Yan Chen

The Polytechnic School Arizona State University

arXiv:2203.10939v2 [cs.CV] 5 Jul 2022

## Hongbin Yu

School of Electrical, Computer and Energy Engineering Arizona State University

**ABSTRACT**

This paper explores Deep Learning (DL) methods that are used or have the potential to be used for traffic video analysis, emphasizing driving safety for both Autonomous Vehicles (AVs) and human- operated vehicles. We present a typical processing pipeline, which can be used to understand and in- terpret traffic videos by extracting operational safety metrics and providing general hints and guide- lines to improve traffic safety. This processing framework includes several steps, including video enhancement, video stabilization, semantic and incident segmentation, object detection and classifi- cation, trajectory extraction, speed estimation, event analysis, modeling and anomaly detection. Our main goal is to guide traffic analysts to develop their own custom-built processing frameworks by selecting the best choices for each step and offering new designs for the lacking modules by provid- ing a comparative analysis of the most successful conventional and DL-based algorithms proposed for each step. We also review existing open-source tools and public datasets that can help train DL models. To be more specific, we review exemplary traffic problems and mentioned requires steps for each problem. Besides, we investigate connections to the closely related research areas of drivers’ cognition evaluation, Crowd-sourcing-based monitoring systems, Edge Computing in roadside in- frastructures, Automated Driving Systems (ADS)-equipped vehicles, and highlight the missing gaps. Finally, we review commercial implementations of traffic monitoring systems, their future outlook, and open problems and remaining challenges for widespread use of such systems‡.

# Introduction

Despite recent advances in vehicles’ operational safety features, computer-assisted control, and technology-based traffic management systems, traffic safety remains one of the main challenges in today’s life. Every year, traffic crashes account for 20-50 million causalities and 1.35 million fatalities worldwide, making it one of the top-10 causes of death. Indeed, traffic crashes is the leading cause of death for people aged 5 to 29 [[1].](#_bookmark55)

Using computational intelligence and computer tools for enhancing traffic safety has gained a lot of attention in recent years. Mainstream technological trends include (i) implementing vehicle safety features such as forward collision

\*Corresponding author. email: [arazi@clemson.edu](mailto:arazi@clemson.edu)

†These authors contributed equally to this work.

‡This material is based upon the work supported by the National Science Foundation under Grant No. 2008784 and the Arizona Commerce Authority under the Institute of Automated Mobility (IAM) project.

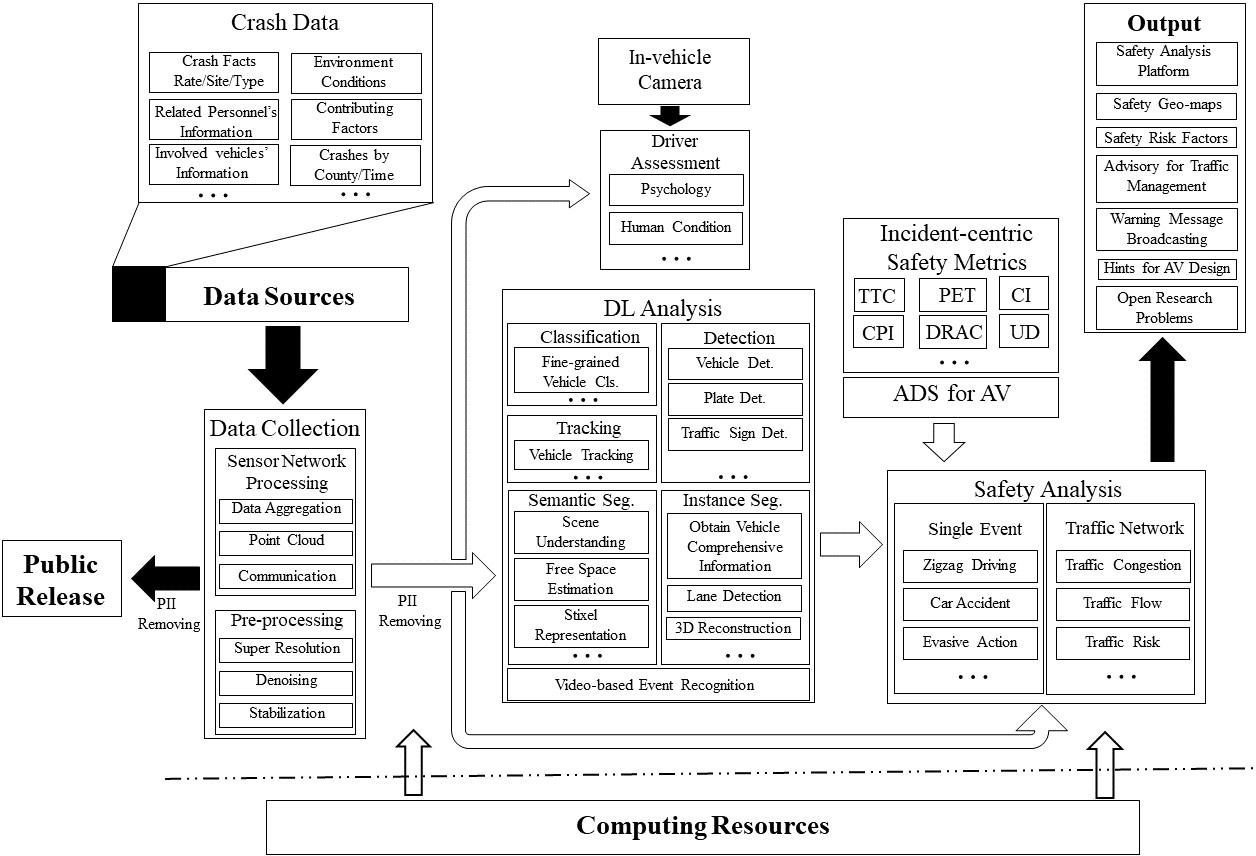


Figure 1: A framework of Computer Vision (CV)-based traffic safety analysis pipeline.

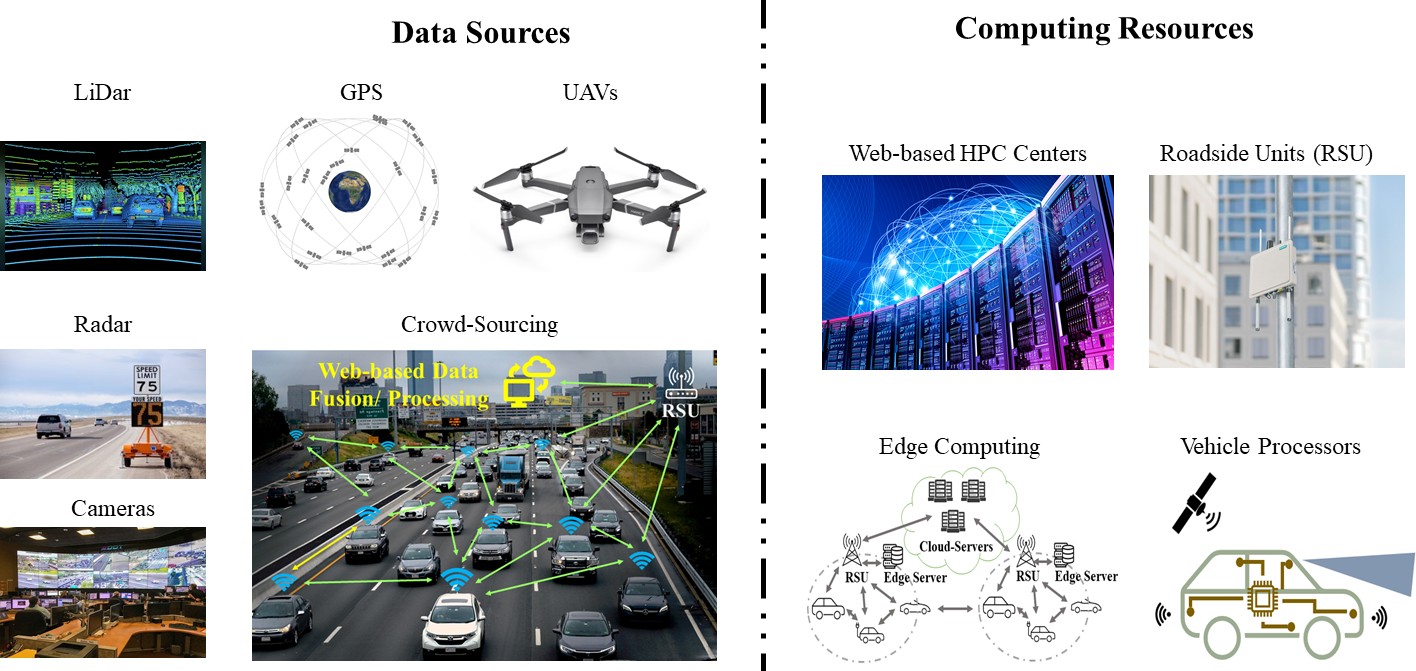


Figure 2: The data sources and computing resources used in video-based traffic analysis.

warning, blind-spot detection, lane departure warning, backup camera, and autonomous emergency braking [[2],](#_bookmark56) (ii) simulation-based road infrastructure design such as Site3D, RoadEng [[3],](#_bookmark57) and OpenRoads Designer [[4],](#_bookmark58) and (iii) intelligent traffic flow management systems such as Global Positioning System (GPS)-based navigation tools. An example of the last category is Google’s road-user interpretive software that can infer the common road behavior of other drivers that allows Engine Control Units (ECUs) to make better route decisions [[5].](#_bookmark59)

Many car manufacturers have developed Artificial Intelligence (AI)-based safety features [[5].](#_bookmark59) Tesla, Audi, and BWM have already developed sensor-based and vision-based perception systems to help the drivers judge road conditions more accurately and use partial autonomy [[6,](#_bookmark60) [7].](#_bookmark61) Particularly, the recent advances in Deep Learning (DL) methods for video processing backed by low-cost and high-speed computational platforms such as Graphics/Tensor Processing Units (GPUs/TPUs) have accelerated the pace of developing AI-based features both at vehicle and infrastructure levels [[8].](#_bookmark62)

Commercial transportation has witnessed unprecedented growth in utilizing autonomous driving systems, in recent years. Waymo launched a self-driving taxi service in Phoenix, Arizona in 2020 [[9].](#_bookmark63) Almost the same time, General Motors (GM) presented their prototype for autonomous buses [[10].](#_bookmark64) Meanwhile, Amazon revealed their future public transportation plan, which offers passengers-only compact autonomous shuttles [[11].](#_bookmark65) Starship robots [[12]](#_bookmark66) and Nuro’s autonomous delivery bots [[13]](#_bookmark67) are other examples of AI-based commercial traffic platforms. The autonomous semi- truck concept, independently presented by Tesla and Waymo [[14,](#_bookmark68) [15],](#_bookmark69) brings tons of benefits to logistic and cold chain monitoring, building a solid fundamental for industry traffic.

In the industry domain, camera-based traffic monitoring systems have been broadly used to detect incidents and apply congestion control [[16,](#_bookmark70) [17].](#_bookmark71) Sensor-based adaptive traffic light control systems are used to reduce traffic jams [[18,](#_bookmark72) [19,](#_bookmark73) [20].](#_bookmark74) Modern systems use Vehicle-To-Vehicle (V2V) and Vehicle-To-Infrastructure (V2I) communications to enhance the overall driving safety. For instance, Roadside Unit (RSU)-based radar systems with real-time data analysis are used to monitor pedestrians on the road and minimize crash rates by sending alerts to connected vehicles [[21].](#_bookmark75) These technologies have optimized existing infrastructures and greatly increased traffic safety.

## Architectural View

Traffic Safety analysis can be viewed as a modular and multi-faceted problem that involves many aspects. As shown in Figs. [1](#_bookmark1) and [2,](#_bookmark2) the overall analysis platform can be viewed as a software pipeline where the collected information undergoes different processing steps until it is translated to navigation commands, advisory messages, or overall guidelines for improving traffic safety.

This paper provides a comprehensive review of the popular methods, tools, software packages, and datasets developed by the scientific community for each vision-based sub-problem. We also highlight the open problems and future challenges on each frontier. Our main emphasis is on the role of vision-based DL methods in enhancing traffic flow (e.g., improving efficiency) and mitigating traffic safety risks.

In contrast to the primary trend of processing individual events from an involved vehicle’s perspective, we consider traffic safety at both the vehicle-level and network-level by processing videos captured by an external observer. The main information source is captured video by vehicle-mounted cameras and roadside cameras, but we also will review other sensor information that can be used for traffic management. We believe that enabling advanced traffic safety analysis and monitoring platforms will play a crucial role in future smart cities. [Fig.3](#_bookmark4) compares video-analysis from two different perspectives, from an external point of view as well as an internal node’s perspective.

Table 1: Summary of related review papers. The paper with ’\*’ means although this paper is related but outdated. *L*√

denotes a topic is covered in fewer details.

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Paper** | [[22]](#_bookmark76)Hu et al. | [[23]](#_bookmark77)Mozaffari et al. | [[24]](#_bookmark78)Grigorescu et al. | [[25]](#_bookmark79)Yurtsever et al. | [[26]](#_bookmark80)Janai et al. | [[27]](#_bookmark81)Badue et al. | [[28]](#_bookmark82)kumaran et al. | [[29]](#_bookmark83)Wang et al. | [[30]](#_bookmark84)Nguyen et al. | [\*[31]shirazi](#_bookmark85) et al. | [\*[32]Mukhtar](#_bookmark86) et al. | [\*[33]](#_bookmark87) Morris et al. | Ours |
| **Year** | 2020 | 2020 | 2020 | 2020 | 2020 | 2020 | 2019 | 2019 | 2018 | 2016 | 2015 | 2013 |  |
| **Human-driven Vehicle** | √ | √ |  | √ |  |  | √ | √ | √ | √ | √ | √ | √ |
| **AVs** | √ | √ | √ | √ | √ | √ | √ |  | *L*√ |  |  |  | √ |
| **Safety Assessment Analysis** | √ | √ | √ | √ |  |  | √ |  |  | √ |  | √ | √ |
| **CV-based Method** | √ | *L*√ | √ | √ | √ | √ | √ | √ | *L*√ | √ | √ | √ | √ |
| **Deep Learning Method** | *L*√ | √ | √ | √ | √ | *L*√ | √ | √ | *L*√ |  |  |  | √ |
| **Sensors** √ | |  | √ | √ | √ | √ |  |  |  | √ | √ |  | √ |
| **Datasets** | |  | √ | √ | √ |  | √ |  |  | √ |  | √ | √ |

**Network Analysis**

**Vehicular Edge Computing**

**Behavioral & Driver Cognition**

√ √ √ √ √ √ √

√

√



Figure 3: The example of Perspectives: (a) Internal Perspective and (b) External Perspective.

Table 2: Specific details on the shortcomings of the most recent survey papers in CV-based traffic analysis.

**Survey Content Drawback Perspective Application**

[[22](2020)](#_bookmark76)

Review existing research works on traffic conflicts based on perception technologies and communication technologies.

Discusses very limited DL methods (covers less than 10 DL methods); covers in fewer details the CV tasks

(including detection, trajectory extraction, and video analysis).

Internal AVs

[[23](2020)](#_bookmark77)

[[24](2020)](#_bookmark78)

[[25](2020)](#_bookmark79)

Reviews DL approaches for Trajectory prediction based on the input representation, output type, and prediction method.

Reviews DL approaches (mainly as CNN, RNN, Deep Reinforcement Learning) for AVs; partially discusses safety assessment.

Reviews practical challenges and solutions for Avs; the main tasks involve localization, mapping, perception, planning, and human-machine interfaces; emphasizes the whole driving system architecture.

Because of the limited works focusing on CV data (e.g. BEV), it only discusses 6 (CNN)+4 (CNN+RNN) methods.

shallowly covers sensor information;

less details are provided for performance comparison (only covers 10 detection methods on a general dataset and 4 semantic segmentation methods on CityScapes).

Excludes video pre-processing methods (e.g., Video stabilization); provides little details on the performance analysis

(9 methods on ImageNet and 7 methods on KITTI 3D).

External Avs; traffic analysis

Internal AVs

Internal AVs

[[26](2020)](#_bookmark80)

[[27](2020)](#_bookmark81)

[[28](2019)](#_bookmark82)

[[29](2019)](#_bookmark83)

Reviews CV-based approaches for AVs; discusses open problems and current challenges.

Reviews technologies for the perception and decision-making system of Avs;

discusses the AV industry milestones.

Reviews approaches for

anomaly detection for surveillance videos.

Reviews DL approaches for multiple traffic applications, including time series prediction,

classification, and optimization.

Lacks the safety assessment analysis;

does not give detailed performance comparisons.

Covers limited DL methods (sign and light detection, pavement marking detection,

MOT, excluding segmentation methods);

does not give detailed performance comparisons.

Only includes tasks related to anomaly detection; does not include other CV tasks;

does not provide comprehensive performance analysis.

Covers a few CV-based problems (including traffic sign recognition, vehicle detection, and pedestrian detection,

excluding MOT and segmentation); offers a limitted comparative analysis

(including only the traffic sign and traffic flow prediction).

Internal AVs

Internal AVs

External Traffic analysis

External AVs; traffic analysis

[[30](2018)](#_bookmark84) Reviews DL approaches for processing traffic data. Covers a few CV-based problems (including vehicle detection,

perception on Avs, etc,.) without sufficient detail.

External Traffic analysis

It is noteworthy that several review papers have been published to review methods and tools used for video-based traffic analysis. A summary of these papers is provided in Table [1.](#_bookmark3) However, most review papers have limitations in certain aspects.

Some survey papers (e.g., [[25,](#_bookmark79) [26,](#_bookmark80) [27,](#_bookmark81) [29,](#_bookmark83) [30])](#_bookmark84) focused merely on solving traffic-related tasks (such as perception) while not covering safety assessment methods. Some other papers (e.g., [[22,](#_bookmark76) [27])](#_bookmark81) do not provide a comprehensive summary of DL methods, which recently has become the dominant approach in both industry and academia research. Other papers (e.g., [[25,](#_bookmark79) [26,](#_bookmark80) [27]),](#_bookmark81) which review driving techniques for vehicles equipped with Automated Driving Systems (ADS), keep their attention solely on the DL methods developed for AVs while not investigating the practi- cality of these methods on human-driven vehicles, which still are the most widely used vehicles. A few papers (e.g.,

[[28,](#_bookmark82) [22])](#_bookmark76) put their primary focus on DL methods but without special emphasis on vision-related tasks particularly useful for traffic analysis. A different set of papers (e.g., [[23])](#_bookmark77) limit their analysis to the perspective of internal nodes, also known as the first-person perspective. Although Computer Vision (CV)-based tasks are covered by several papers [[29,](#_bookmark83) [30],](#_bookmark84) they do not provide sufficient details on this subject from different perspectives. Most of the papers, includ- ing [[24,](#_bookmark78) [26,](#_bookmark80) [27,](#_bookmark81) [28,](#_bookmark82) [30],](#_bookmark84) although very informative, only review the DL algorithms that are used or can be used for traffic analysis and do not provide any sort of comparative analysis, which does not help choosing the right method for different real-world traffic problems. The relevant surveys we include are from 2013 and after; however, we want to mention some papers, including [[31,](#_bookmark85) [32,](#_bookmark86) [33]](#_bookmark87) are outdated, but highly related to our survey with the topics of CV-based traffic safety analysis. Table [2](#_bookmark5) provides more specific details on the main focus and the shortcoming of the recently published survey papers.

In addition to covering newly published CV-based methods, our paper covers the shortcomings of previous surveys and considers the video-based driving safety problem from different perspectives. More specifically, we list exemplary problems in video-based driving safety analysis; we review requirements and challenges from an external observer’s perspective; we review datasets and important industrial developments; we make connections to closely related areas of utilizing crowd-sourcing, and edge and cloud computing for bulk processing; we highlight connections to behavioral science, insurance industry, and other policy maker entities.

The rest of this paper is organized as follows. Section [2](#_bookmark6) reviews mainstream lines of DL methods used for vision- based driving safety analysis. In Section [3,](#_bookmark9) data acquisition equipment and methods are reviewed. Section [4](#_bookmark11) includes discussions about different stages of video pre-processing for safety analysis by highlighting historical milestones, successful methods, current trends, and remaining challenges for each category. Section [5](#_bookmark13) reviews DL methods for video processing with application to traffic safety analysis. A short list of sample problems in driving safety analysis is provided in Section [6.](#_bookmark33) Section [7](#_bookmark37) reviews recent trends in deep learning that can influence the field if video-based driving safety analysis. A list of commonly used datasets with applications to traffic monitoring and traffic safety analysis is provided in Section [8.](#_bookmark43) Section [9](#_bookmark48) list a set of key safety metrics used for assessing the potential for crash occurrence and crash severity. Section [10](#_bookmark49) provides different key points such as connection to other fields and potential applications of safety analysis methods. A roadmap of this technology is offered in Section [11.](#_bookmark52) Remaining challenges and issues are discussed in section [12.](#_bookmark54)

# Deep Learning Methods

The common core of vision-based driving safety analyses is using deep learning methods for image/video processing. We skip the details of DL methods here for the sake of brevity and refer the interested reader to previous reviews [[34,](#_bookmark88) [35].](#_bookmark89)

It is noteworthy that most of the recent developments in DL have been driven by two applications, Computer Vision (CV), and Natural Language Processing (NLP), as two key representatives of visual and sequential processing prob- lems. Most elegantly designed DL platforms utilize Multilayer Perceptron (MLP), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and transformers as their building blocks. Table [3](#_bookmark7) provides a compact and informative comparison of these methods. We will provide a more detailed analysis of custom-built DL methods used in the context of driving video analysis and safety control.

Table 3: A brief comparison among typical DL architectures.

**Architecture MLP CNN RNN/LSTM Transformer**

Pros Straightforward to design

Many parameters (dense connections) Limited capability

Cons

Appropriate for high-dimensional data Learns features with locality

Shift-invariance Fewer parameters Powerful on CV tasks

Do not encode the position of object Gradient vanishing in deep architectures (solved by ResNet and auxiliary output) Weak on long sequential data

Appropriate for sequential data Can learn long-term dependencies

Hard to train for gradient issues Handles only serially fed data

Powerless on extreme long-term dependencies

Processes sequences in parallel Appropriate for long sequences Captures long-term dependencies Enables self-attention mechanism Powerful on both CV and NLP tasks

Many parameters (long training time) Does not consider locality

Over complicated for short sequences

Inductive Bias Weak Locality/spatial invariance Sequentiality/time invariance Weak

Training a network is not always straightforward and can be impacted by many factors, such as hyper-parameters (mini-batch size and learning rate). Due to the time sensitivity of safety-related applications, fast training is a key requirement. Table [4](#_bookmark8) lists some common tricks (e.g., dropout, regularization, easy-derivative Rectified Linear Unit (ReLU) and leaky ReLU activation function, data augmentation, and soft labeling) to accelerate the training pro- cess and boost the recognition performance. For example, word embedding uses low-dimensional space to present high-dimensional data allowing words with similar meanings to be closer in the low-dimensional space. This often

Table 4: Common tricks to accelerate DL training.

**Name Description**

Data Normalization Stabilize the training

Xavier/Kaiming Initi. Initialize based on the magnitudes of signals

Batch/Layer/Instance Normalization

Local response normalization Regularize

Avoid gradient vanishing

Reduce number of parameters Avoid overfitting

Dropout

L1/L2 regularization Avoid overfitting

Similar to L2 regularization

Weight decay

but different in some optimizers (e.g. Adam)

LeakyRelu Avoid dead neurons (as for Relu) Word Embedding Manage high-space categorical data

State the relations between different classes; Improve generalization

Soft Labeling

Data Augmentation

Improve the variety of data Improve generalization

Avoid gradient vanishing

Residual Connection

Allow building very deep networks

1 × 1 Conv Combine channels Gradient Clipping Avoid gradient explosion

outperforms the one-hot encoding. Such tricks can be translated from the NLP context to driving behavior analysis. An exemplary scenario would be the personalized driving anomaly detection. Suppose there are 20 collected features for each driver. If there are 100 drivers, by one-hot encoding, the input dimensions of data should be 100 + 20 = 120 per time point, which leads to the *curse of dimensionality*. In fact, difference among different drivers (or driving styles) can be well represented by as few as 20 dimensions.

# Data Acquisition

In this section, we investigate the role of data acquisition in developing safety-related algorithms. First, we review data modalities and hardware used for information acquisition. Next, we list the most commonly used datasets for testing the developed algorithms.

Most traffic analysis platforms rely on data collected by different types of sensors, including cameras, Global Position- ing Systems (GPS), Radio Detection And Ranging (Radar), and Light Detection and Ranging (LiDAR). These sensors (except GPS) can be used in vehicles or on external observer systems such as roadside infrastructures, drone-based aerial platforms, etc. The following is a short description of sensors followed by a summary provided in Table [5.](#_bookmark10)

**Video Cameras** are the most widely used means of information collection. Modern cars are heavily equipped with cameras in various parts to capture imagery for processing. Using thermographic cameras for night vision has become more common than ever. Camera feeds can be used by the driver (e.g., backup camera) to minimize safety risks, or by the control computer in an AV for automated driving. The imagery can also be used by more advanced AI platforms for driver’s cognition assessment in real-time mode (e.g., driver drowsiness assessment [[36],](#_bookmark90) and distraction awareness [[37]).](#_bookmark91) Volume collections of imagery can be stored for further analysis for transportation infrastructure revisions.

**GPS** systems provide an accurate position of the vehicle by communicating to GPS satellites. The accuracy of GPS depends on different factors, including satellite geometry, signal blockage, atmospheric conditions, and receiver design features/quality. The global average User Range Error (URE) of GPS can be as low as 2.3 [ft[38].](#_bookmark92) With recent advances in 5G wireless networking, even preciser positioning is available for vehicles. For instance, Verizon launched its Hyper Precise Location (HPL) using Real-Time Kinematics (RTK), with an unprecedented accuracy of 1-2 [centimeters[39].](#_bookmark93)

**Radar** operates based on Doppler frequency shift in the reflected wave [[40].](#_bookmark94) Radar units are often installed on modern cars, roadside poles, police vehicles, and portable speedometer guns to measure the absolute or the relative speed of other vehicles. Radars are low-cost and relatively robust devices appropriate for different weather conditions and illumination intensities. Some radar units may have a narrow Field of View (FoV) but are capable of long-range detection [[31].](#_bookmark85) A traditional radar is a single source-detector, which does not have the spatial resolution required for

precise scene/environment description; however, in recent years, imaging radars have been developed by adopting multiple-input, multiple-output (MIMO), and radar-on-chip technologies. Although such advanced technology is still expensive, attempts are made to reduce the cost of broader [adoption[41].](#_bookmark95)

**LiDAR** uses laser beam reflection to enable accurate positioning down to centimeter’s scale [[42].](#_bookmark96) The 3D scanning of multiple laser beams provides a 3D point cloud image (3D map) of the surrounding obstacles with accuracy much higher than regular radars [[43].](#_bookmark97) LiDARs send out a near-infrared laser beam and detect reflections from the object; thus, it can still operate in dark conditions, in contrast to visual sensors. Its use is less common than radars for a few reasons, including its higher cost, relatively sparse spatial resolution, especially for a limited number of scanning laser beams, extremely narrow FoV, and computational complexity of 360◦ scanning, noting that low-complexity

point cloud methods are still under development. Solid-state LiDARs have been developed to reduce the cost, while

enhancing the spatial [resolution[44].](#_bookmark98)

**Drones** are commonly used nowadays to implement aerial monitoring systems. Most external observer systems utilize sensors in roadside infrastructures. However, the use of drones, also known as Unmanned Aerial Vehicles (UAVs), is gaining more attention in different applications to enable fast, low-cost, and on-demand monitoring [[45],](#_bookmark99) and traffic analysis is not an exception. Particularly, drones can provide top-view and clearer occlusion-free images of the traffic flow when needed [[46].](#_bookmark100) A network of cooperative drones can collectively cover relatively large areas [[47].](#_bookmark101) Modern drones may be equipped with advanced sensing platforms, high-resolution cameras, and more importantly advanced features such as learning-based image processing, AI-based autonomous control, collision avoidance and auto lading, auto-calibration, real-time transmission, object tracking, and image restoration. The key challenges of drones are their limited payload, flight time, and communication range under study by several research teams. Aerial images pose new challenges to the research community, such as tackling image stabilization, small object recognition, and developing lightweight ML algorithms customized for top-view images.

**Other Sensors:** In addition to the aforementioned broadly-used sensors, there exist some custom-built advanced sensors that can be used for traffic monitoring and driving safety analysis. Passive Infrared [sensors[48],](#_bookmark102) Inductive [Loops[49],](#_bookmark103) and Piezoelectric sens[ors[50]](#_bookmark104) can enable measuring basic flow parameters such as vehicle count, speed, and flow volume, noting that Piezoelectric sensors are still used for weigh-in-motion measurement. Environmental Sensor Stations [(ESS)[51]](#_bookmark105) on the roadway can collect atmospheric data, including air temperature and humidity, visibility distance, wind speed, wind direction, etc., as side parameters to be used for traffic analysis.

Table 5: Comparison of sensors. Here “√” means this kind of measure has been implemented or available to complete.

Count

|  |  |  |
| --- | --- | --- |
| **Sensor Type Measures Type Cost**  Vehicle Speed/Distance Vehicle Pedestrian Road feature | **Shape Robust to Modeling Bad Environment**§ | |
| Camera (Visible) √ Hard √ √ √ Low | 2D | Low |
| Camera (Infrared) √ Hard √ √ √ Low | 2D | High |
| LiDAR √ Easy √ √ √ High | 3D | Middle |
| Radar √ Easy √ Moderate | weak | High |
| UAV Camera √ Moderate √ √ √ Low | 2D | Low |

Estimation

Classification

Detection

We recognize that the properties of sensors are varied. For example, visual cameras require clean and high-visible environments and offer a richer set of information in terms of color space and visual geometry, hence are more ap- propriate for detection and classification applications. However, interpreting imagery may require more computation powers. LiDARs, on the other hand, provide more accurate precision for object detection and depth and speed esti- mation but are expensive and less energy efficient. Some manufacturers like Tesla prefer pure vision-based perception [[52].](#_bookmark106) However, fusing multiple sensors can be advantageous from the safety perspective and is adopted by more vendors, as discussed in [[53].](#_bookmark107)

# Video and Image Pre-processing

In this section, we review different stages of a typical video-based traffic analysis framework and highlight key devel- opments, historical milestones, current trends, and existing challenges.

**Super Resolution**: The video and image super-resolution aims to reconstruct a Higher Resolution (HR) result from a Low Resolution (LR) observation. Super-resolution is a typical stage in image pre-processing and can be applied to traffic imagery to enhance the performance of the subsequent learning tasks, such as vehicle classification and license

§Noting that visual cameras may perform poorly under low illumination, and both visual cameras and LiDARs are limited by the bad weather, such as fog, dust, rain, or snow.

plate detection. One popular supervised learning method is the DL-based Single Image Super-Resolution (SISR) method which creates a mapping between the low and high-resolution images by training a deep CNN. Most of the existing learning-based SISR methods are trained and evaluated using simulated datasets [[54,](#_bookmark108) [55,](#_bookmark109) [56,](#_bookmark110) [57],](#_bookmark111) where the LR images are generated by applying a hand-crafted degradation process into the HR samples. For instance, one may apply bi-cubic down-sampling to the original HR samples to obtain LR results. Recently, more advanced SISR [[58]](#_bookmark112) methods are developed for real-world applications with unknown and more complicated degradation processes, which can be used as a benchmark method for traffic image analysis as well.

In contrast to the simple spatial interpolation used in the SISR family for image processing, Video Super-Resolution (VSR) methods utilize both spatial and temporal relationships between consecutive frames to improve the quality of the reconstructed [videos[59].](#_bookmark113) These methods are essential in processing roadside traffic videos, especially under poor visibility in foggy, rainy, and cloudy weather conditions.

An important application of SR methods is license plate detection for vehicle identification. Early works often focused on conventional signal processing methods. For instance, [[60,](#_bookmark114) [61]](#_bookmark115) deployed a Markov random fields-based method for plate detection. [[62]](#_bookmark116) proposed a Gaussian Mixture Model (GMM) to enhance the plate location and SR reconstruction. Compressed Sensing (CS)-based [methods[63,](#_bookmark117) [64,](#_bookmark118) [65]](#_bookmark119) can also be used to address this task by enforcing the sparsity of images in the frequency domain, which is equivalent to smoothness in the spatial domain. Recently, DL-based SR algorithms are proposed, which perform more accurately and efficiently. [[66]](#_bookmark120) is an example of such methods which use a CNN architecture to convert a low-resolution license plate into a high-resolution version. Some recent works [[67,](#_bookmark121) [68,](#_bookmark122) [69,](#_bookmark123) [70]](#_bookmark124) tend to use Generative Adversarial Networks (GAN) as their processing framework, which achieves a higher performance using a more reasonable real-time loss along with an adversarial loss, when inferring.

**Denoising**: This is another critical pre-processing task to compensate for imaging artifacts and obtain clear and noise- free images before feeding them into the subsequent learning modules. This is a critical step in processing traffic imagery, especially when taken in motion or under low illumination and poor environmental conditions like rainy, cloudy, and foggy weather.

Conventional methods typically use filtering, interpolation, and smoothing methods either in time, frequency, or wavelet domains to remove noise from the captured images. In contrast, newer methods use more advanced con- cepts such as sparsity in the frequency domain, dictionary learning to model common noise patterns, prior knowledge about the noise model, and noise pattern discovery to more elegantly remove the noise from the captured images.

Traditional methods suffer from several shortcomings, including (1) involving complex optimization methods in some cases, (2) the need for manual parameter setting (e.g., the scale factor of Gaussian spatial filtering), (3) and using a fixed model which deems inflexible in tackling different noise patterns and ignore the learnability of some noises.

DL-based video and image denoising algorithms take advantage of the neural networks to learn the spatial or temporal dependency between pixels to reconstruct clean samples by end2end training and inferring. Therefore, DL methods provide sufficient flexibility in adapting to different conditions. In most research works on image denoising, a synthetic Additive white Gaussian Noise (AWGN) model is adopted to simulate the noise and evaluate the algorithm. Using a synthetic AWGN noise model has the clear advantage of simplifying the testing phase and quantifying the noise impact. However, it might oversimplify the problem since the real-world noise models can be more complicated depending on the noise source. Further, one may benefit from exploiting common noise patterns for more structured noises. For instance, the noise caused by rainy conditions may need a different treatment than a noise caused by the camera lens scratch. For instance, [[71,](#_bookmark125) [72]](#_bookmark126) generates noisy and clean image pairs by controlling the ISO (sensitivity to light) of the cameras. By these approaches, the collected data could be used to emulate the camera-related noise under real-world conditions.

Similar to SR methods, denoising methods are typically used for generating clean traffic images that could be used to improve the precision of higher-level tasks. For example, in [[73],](#_bookmark127) a low-rank decomposition image denoising method is proposed for restoring the noisy traffic image. Likewise, in [[74],](#_bookmark128) spatio-temporally denoised images are used to enhance the performance of the traffic incident detection algorithm.

**Video Stabilization**: Traffic videos may contain vibrations, especially when captured by vehicle dashboard-cameras while driving on rough roads. This may underline the performance of the subsequent processing stages (e.g., vehicle detection, speed estimation, etc.). Digital video stabilization techniques are proposed to improve the visual quality of the captured videos [[90,](#_bookmark144) [91].](#_bookmark145) The common spirit of most video stabilization methods is extracting trajectory of objects or their representative feature points between consecutive frames, and the re-aligning the frames to smooth out the trajectories, based on the assumption that noise-like high-frequency fluctuations, especially when shared among most image descriptors, are caused by the camera shakes. We can subdivide these methods into pixel-based and feature-based methods. The pixel-based methods typically use block matching [[92,](#_bookmark146) [93],](#_bookmark147) phase information [[94,](#_bookmark148) [95],](#_bookmark149) and optical flow [[96,](#_bookmark150) [97]](#_bookmark151) to estimate the camera motion. Feature point detection methods can be used to convert

Table 6: Examples of fine-grained vehicle classification.

|  |  |  |
| --- | --- | --- |
| **Method** | **Paper:[Ref] Authors (year)** | **Performance Accuracy [Dataset]** |
| 3D box+CNN | [[75]](#_bookmark129)Sochor et al.(2016) | 83.20% on BoxCars116k(self) |
| 3D box+Vgg-16 | [[76]](#_bookmark130)Sochor et al.(2018) | 92.27% on BoxCars116k(self) |

DenseNet-161 [[77]Ma](#_bookmark131) et al.(2020) 93.81 % on Stanford [Cars[78]](#_bookmark132)

97.89 % on [COMPCARS[79]](#_bookmark133)

DenseNet-161 [[80]Li](#_bookmark134) et al.(2019) 93.51% on Stanford [Cars[78]](#_bookmark132)

|  |  |  |
| --- | --- | --- |
| part-based +DenseNet-264 | [[81]](#_bookmark135)Xiang et al.(2019) | 94.3% on Stanford [Cars[78]](#_bookmark132) 99.6% on [COMPCARS[79]](#_bookmark133) |
| Part-based+RCNN+SVM | [[82]](#_bookmark136)Huang et al.(2016) | 87.3% |
| Faster R-CNN+Feature Fusion | [[83]](#_bookmark137)Zhu et al.(2019) | Top 1: 79.1%, Top 5: 94.1% on [COMPCARS[79]](#_bookmark133) |
| CNN+Feature Fusion | [[84]](#_bookmark138)Yu et al.(2018) | 98.89% on [COMPCARS[79]](#_bookmark133) |
| ResNet-50 + Attention | [[85]](#_bookmark139)Yu et al.(2020) | 93.1% on Stanford [Cars[78]](#_bookmark132) 95.3% on [COMPCARS[79]](#_bookmark133) |
| Attention | [[86]](#_bookmark140)Ke et al.(2020) | 94.5% mAP on Stanford [Cars[78]](#_bookmark132) 95.8% FZU dataset (self) |
| multi-task CNN | [[87]](#_bookmark141)Hu et al.(2017) | Top 1: 91%, Top 5: 97.7% on [COMPCARS[79]](#_bookmark133) |
| CNN+filter bank | [[88]](#_bookmark142)Wang et al.(2018) | 93.8% on Stanford [Cars[78]](#_bookmark132) |
| Fine-tuning Vgg-16 | [[89]](#_bookmark143)Zhang et al.(2018) | 98.71% on [COMPCARS[79]](#_bookmark133) |

high-dimensional images into low-dimensional representations to reduce the computation overhead. In [[98],](#_bookmark152) Scale- Invariant Feature Transform (SIFT) [[99],](#_bookmark153) Speeded Up Robust Features (SURF) [[100],](#_bookmark154) and other feature point extraction methods are compared for evaluating their impacts on video stabilization. Due to the computational complexity of video stabilization methods, it is often performed offline, which may not satisfy the requirements of real-time video- processing tasks. Recently, DL-based methods [[101,](#_bookmark155) [102,](#_bookmark156) [103]](#_bookmark157) enable fast and accurate online stabilization in almost a real-time fashion by instant processing of each incoming video frame with low latency.

Most DL-based methods utilize CNN and similar architectures for video stabilization using various sources of traffic data. In [[104,](#_bookmark158) [105,](#_bookmark159) [106],](#_bookmark160) video stabilization was used for aligning the car-mounted camera captured videos. In [[107],](#_bookmark161) the stabled UAV captured videos were used to obtain higher accuracy for traffic video analysis.

# Deep Learning for video processing

Deep learning methods are heavily used for video processing for their outstanding power in solving different problems such as object detection, object recognition, event recognition, and other video understanding tasks in general. DL methods can be considered the brainpower of most AI platforms developed for video-based traffic safety analysis.

## DL-based Classification Methods in Traffic Analysis

Classification is one of the most fundamental tasks in computer vision. The use of classification in this context can be implemented for object classification (e.g., classifying objects between vehicles, pedestrians, motorcycles, traffic signs, etc.), traffic light and railroad crossing barrier status check, and scene detection (e.g., buildings, roads, road lanes, roadside infrastructures, etc.). Often, it is the backbone or the feature extractor part of the detection networks (e.g., [SSD[108])](#_bookmark162) and segmentation networks (e.g., Mask [R-CNN[109]).](#_bookmark163) It can be developed at different levels, such as the basic level for classifying different object types and fine-grained classification into sub-categories (such as differ- entiating traffic signs or identifying vehicle classes among sedans, SUVs, trucks, etc.) based on the semantic content of the input. The well-known baseline classification methods include AlexNet(2012) [[110],](#_bookmark164) VggNet(2014) [[111],](#_bookmark165) GoogleNet(2015) [[112],](#_bookmark166) ResNet(2016) [[113],](#_bookmark167) MobileNets(2017) [[114],](#_bookmark168) [DenseNet(2017)[115],](#_bookmark169) EfficientNet(2019),

[[116]](#_bookmark170) etc. It is noteworthy that ResNet is the most highly cited paper in all areas in Google Scholar Metrics 2020, which further proves its extraordinary achievement.

Classification is often considered an upstream task. Therefore, frameworks of the downstream tasks, such as detection, tracking, and segmentation, often use the pre-trained versions of these baselines DL architectures as their backbone to extract the hidden representations. Note that these baseline methods mainly utilized CNN architectures until re- cently, when a framework named *Transformer* has offered a new breed of deep learning methods with even higher performances, as discussed in Section [7.1.](#_bookmark38)

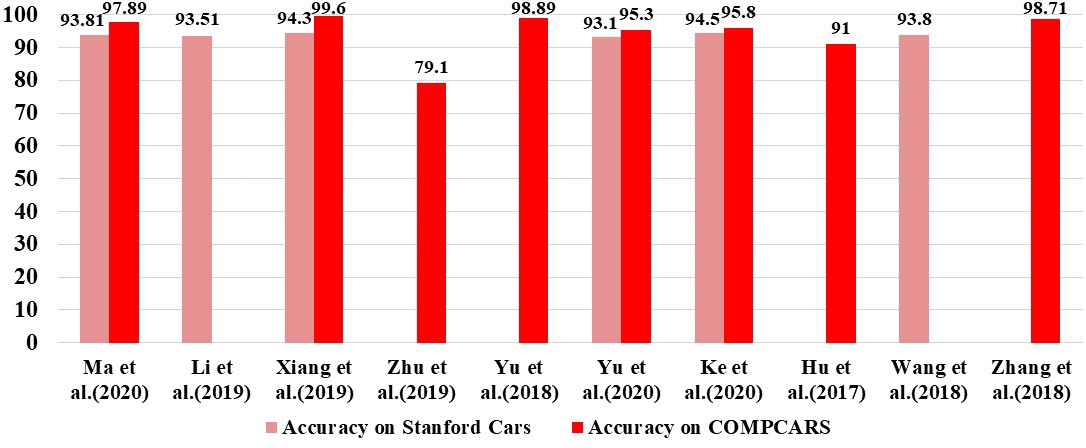


Figure 4: The performance of some fine-grained models on Stanford Cars and COMPCARS.

Since the use of classification methods for most traffic-related problems is straightforward and noting the fact that there exist comprehensive reviews on classification methods, we skip the review of classification methods and refer the interested reader to [[117,](#_bookmark171) [118,](#_bookmark172) [119,](#_bookmark173) [120].](#_bookmark174) Here, we only review fine-grained classification methods that are custom- built or customized for traffic-related problems, as presented in Table [6](#_bookmark12) and [Fig.4.](#_bookmark14)



Figure 5: (a),(b) are the examples of vehicle detection by two alternative methods Y[OLOv5[121]](#_bookmark175) and Faster R- [CNN[122].](#_bookmark176) They output the location and category of each object with detection confidence. Cars are shown by orange bounding boxes, trucks are shown by lime bounding boxes, buses are shown by green bounding boxes, and persons are shown by red bounding boxes. As shown in (a),(b), YOLOv5 performs worse on small vehicle detection while Faster R-CNN has missed objects in the near zone. (c) is the is PII removed data.

## DL-based Object Detection Methods in Traffic Analysis

Object detection is another key stage in DL-based processing pipelines for driving safety analysis. Object detection simply means locating different objects in images and video frames, potentially with complex backgrounds, by draw- ing bounding boxes around the objects of interest.It can coexist or be integrated with object classification and labeling. An illustrative example of vehicle detection using 2 benchmark methods is shown in Fig. [5(a)(b).](#_bookmark15)

Notable examples of object detection in the context of driving safety analysis include detecting surrounding vehicles, humans, traffic signs, and obstacles. It also can be part of more complicated tasks such as traffic distribution and composition analysis, improper lane crossing events, trajectory extraction, speed estimation, moving object tracking, path planning, and detecting vehicles on road shoulders, etc., as presented in Table [15.](#_bookmark34)

Another use case of object detection is removing Personal Identifiable Information (PII), such as masking human face and license plate numbers before publishing traffic video, as shown in Fig. [5(c).](#_bookmark15)

Although there exist some datasets for traffic analysis from the roadside cameras [[123,](#_bookmark177) [124,](#_bookmark178) [125],](#_bookmark179) still there is a critical need for larger datasets that cover different zones, urban, suburban, and rural setups, residential and high-risk zones, railroads, and environmental conditions.

Some notable ongoing research problems include solving the trade-off between the algorithm’s accuracy and speed, realizing small object detection, distributed and federated learning, model sharing among roadside servers, and imple- menting lightweight models and embedded devices appropriate for autonomous vehicles, etc.

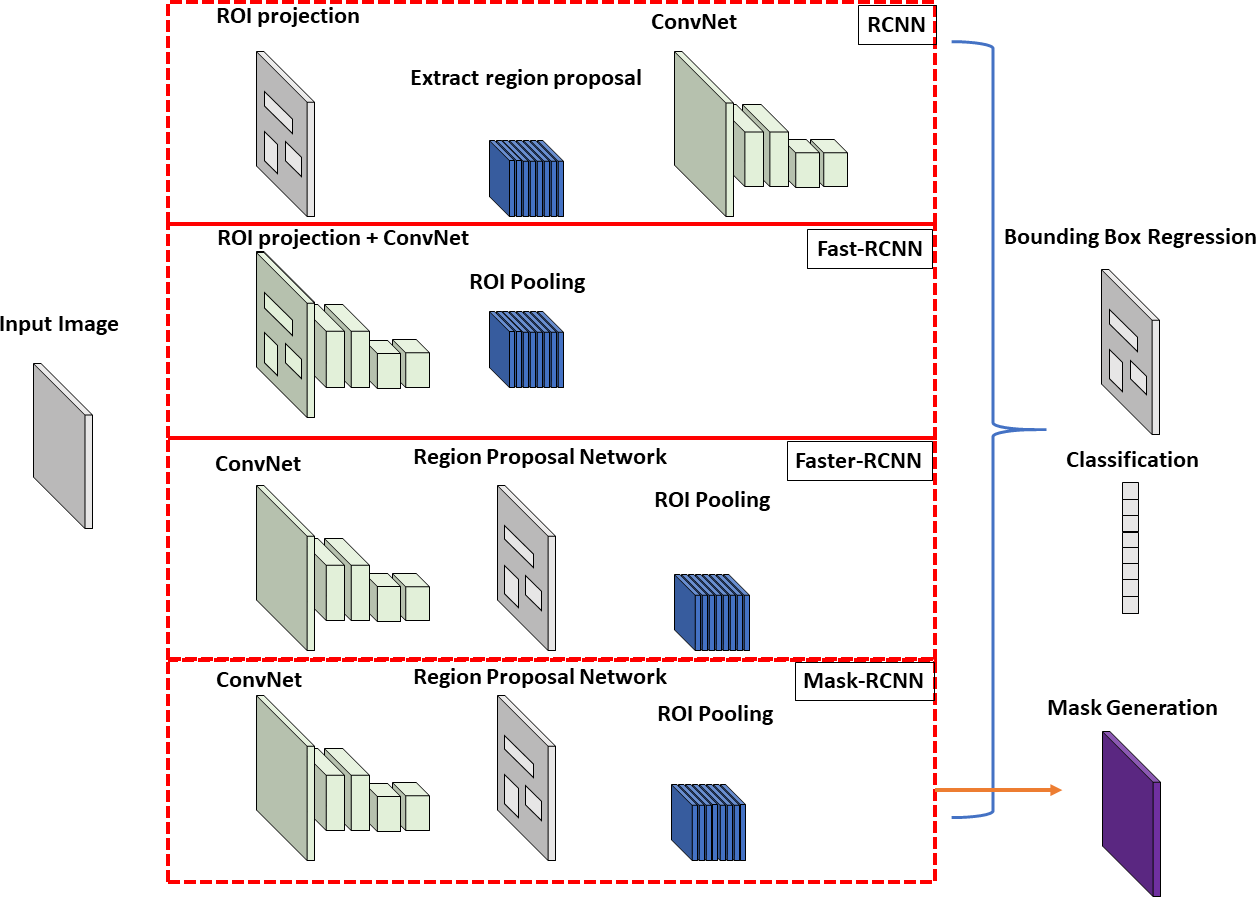


Figure 6: Network architecture for R-CNN family of localization and segmentation.

Compared to the conventional object detection algorithms such as Viola-Jones [detector[126],](#_bookmark180) the Histogram of Ori- ented Gradients (HOG [detector)[127],](#_bookmark181) and Deformable Part-based Models [(DPM)[128]](#_bookmark182) ), CNN-based methods sub- stantially improve the recognition success rate.

From the implementation point of view, the DL-based algorithms can be divided into one-stage and two-stage methods. The two-stage detectors first generate Regions of Interests (RoIs) and then send the region proposals down the pipeline for object classification and bounding-box regression. R-CNN [series[129,](#_bookmark183) [130,](#_bookmark184) [122,](#_bookmark176) [131,](#_bookmark185) [132]](#_bookmark186) comprises the most popular two-stage algorithm family. The architectures of R-CNN series are shown in Fig. [6.](#_bookmark16) Specifically, R-CNN [[129]](#_bookmark183) adopts *Selective Search*[[133]](#_bookmark187) to generate region proposals, and then feed resized (by cropping or warping) proposals into a CNN-based backbone to extract features. Finally, Support Vector Machine (SVM) performs classification for objects’ categories and locations. SPPNet [[134]](#_bookmark188) introduced *Spatial Pyramid Pooling* (SPP) layers, which solved the fixed-size input issue. Integrated by R-CNN and SPPNet, Fast R-CNN [[130]](#_bookmark184) realized *RoI pooling* to output fixed size features and adopted multi-task loss to allow single-stage training. Since Fast R-CNN was still bottlenecked by the *Selective Search* heavy computation, Faster R-CNN [[122]](#_bookmark176) introduced *Region Proposal Network* (RPN), an end-to-end trainable network to generate quality region proposals. Mask R-CNN adds a parallel branch to predict the object mask.

One-stage detectors directly treat object detection tasks as a regression and classification problem. These methods are divided into anchor-free and anchor-based methods. In anchor-based methods, a set of bounding boxes with different predefined sizes are required to capture the scale and aspect ratio of the objects. Some famous implementations include *You Only Look Once* (YOLO) family (e.g., YOLOv2 [[135],](#_bookmark189) Y[OLOv3[136],](#_bookmark190) and Y[OLOv4[137],](#_bookmark191) and YOLOv5 [[121]](#_bookmark175)[¶](#_bookmark0),

¶Note that the authors of YOLOv5 are different from the previous versions

as well as the Single Shot multi-box Detector (SSD) [series[108]).](#_bookmark162) The basic idea of YOLO is demonstrated in Fig.

[7.](#_bookmark17) The network treats the detection as a regression problem and learns the location and class of each bounding box separately. Specifically, an image is split into *S S* patches. In each patch, the network can predict the coordination of *B* bounding boxes with their confidence levels as well as the class of each patch. After aggregation, the bounding box of an object is localized with its category. Then, non-maximal suppression is applied to filter out the extra bounding boxes for the same object.

×

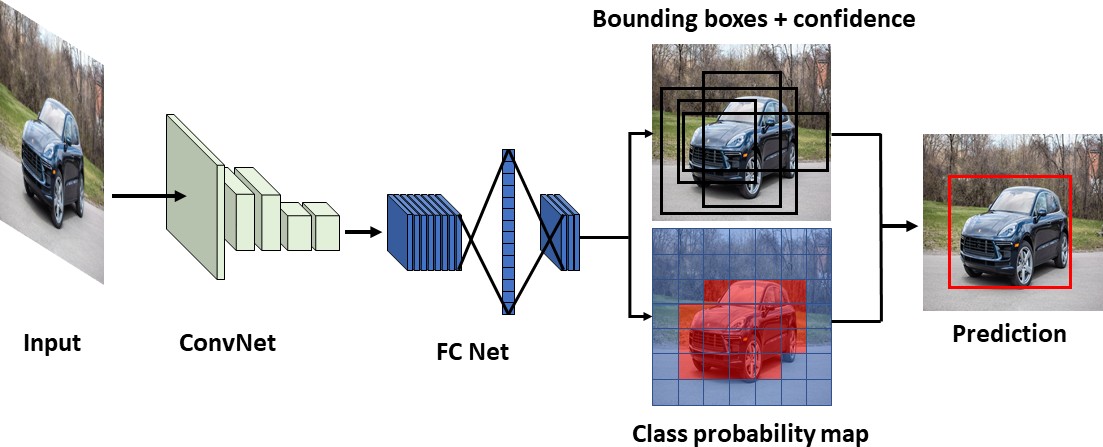


Figure 7: The demonstration of the basic idea of YOLO.

Recently, anchor-free methods are getting more attention to avoid defining anchor-related hyperparameters and to ease complicated computations. The main ideas include implementation by dense prediction (e.g., [DenseBox[138],](#_bookmark192) Fully Convolutional One-Stage (FCOS) object detectors [[139],](#_bookmark193) [RetinaNet[140])](#_bookmark194) as well as implementation by keypoints and center points (e.g., [CornerNet[141,](#_bookmark195) [142],](#_bookmark196) [CenterNet[143,](#_bookmark197) [144],ExtremeNet[145]).](#_bookmark199)

Generally speaking, two-stage methods can achieve higher accuracy but at lower speeds than the one-stage methods. Some recent one-stage methods (including YOLO [v4[137]](#_bookmark191) and [SSD[108])](#_bookmark162) solve the trade-off between the accuracy and speed by realizing a more efficient network structure. A summary of these algorithms’ performance is presented in [Fig.8.](#_bookmark18)

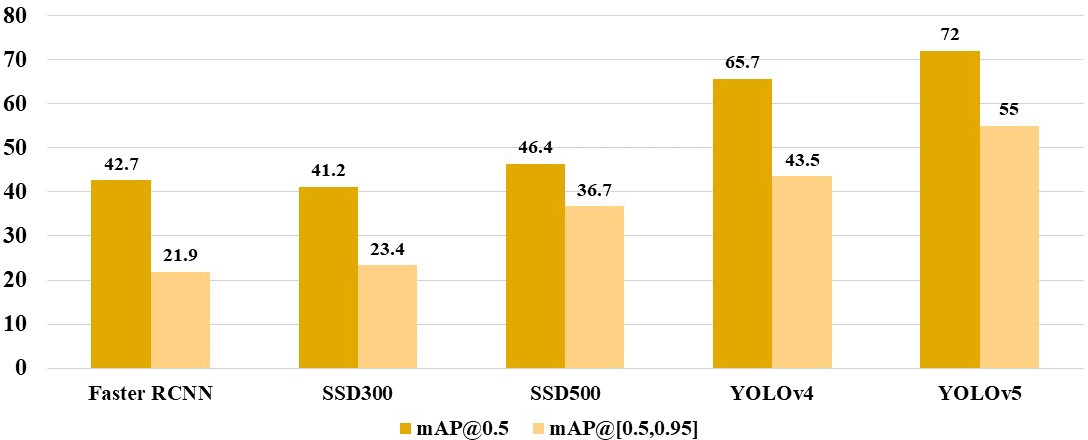


Figure 8: Some object detection models perform on MS COCO test-dev.

The applications of object detection methods in traffic video analysis mostly relate to understanding the objects surrounding the road users, such as vehicles, plates, and traffic signs. Most research works in this area adopt one of the aforementioned algorithms for object detection, as summarized in Table [7.](#_bookmark20) The metrics used for ob- ject detection, recognition, and image segmentation are outlined in Table [9.](#_bookmark22) We note that some works (such as [[146,](#_bookmark200) [147,](#_bookmark201) [148,](#_bookmark202) [149,](#_bookmark203) [150])](#_bookmark204) tend to fine-tune the CNN framework according to the task requirement, and the recent mainstream traffic works begin to deploy the R-CNN series, YOLO series, and SSD widely. It means these algorithms can stand the test of practice, but it does not mean that the other algorithms are not favorable. It also can be due to the relatively low complexity of this task, or due to the difficulty of deploying recent detectors in real-world scenarios.

Pedestrians are often the most vulnerable entities on the road, hence pedestrian detection is usually considered a top- priority component of safety assessment and control systems. Pedestrian detection, especially in crowded areas, would be more complex than similar object detection tasks. Indeed, early CNN-based frameworks underperformed on the task due to the uncertain dense distribution and high dynamics of pedestrians. Some common issues, including the multi- scale problem (different receptive fields with low-information and noisier observations for small-scale pedestrians) and occlusion by crowding (parts of pedestrians are invisible), may challenge these models and decline their accuracy [[151].](#_bookmark205) Some solutions, such as [[152,](#_bookmark206) [153]](#_bookmark207) addresses the multi-scaling issue by modifying the scale of the region proposals. Specifically, [MS-CNN[152]](#_bookmark206) has multiple layers to output features with different receptive fields at the region-proposal sub-network. SAF R-CNN [[153]](#_bookmark207) uses multiple sub-networks to learn the large-scale features and small-scale features, respectively. Likewise, [[154]](#_bookmark208) uses an attention mechanism by applying a fine-grained attention mask to focus on differently scaled pedestrians. SSA-CA [[155]](#_bookmark209) performs detection after semantic segmentation.

Straightforward methods (such as [[156,](#_bookmark210) [157])](#_bookmark211) are proposed to solve the occlusion by enhancing the model to learn patterns with different occlusions. High-level semantic features are employed in [[158,](#_bookmark212) [159]](#_bookmark213) to help the occlusion detection. The other explicit solutions [[160]](#_bookmark214) use data augmentation by introducing extra annotation of the visible parts in the training phase, which substantially enhances the detection ability even under high occlusions. From the author’s perspective, the work in [[161]](#_bookmark215) is very creative, which uses a Cycle-consistent Adversarial Network (Cycle-GAN) [[162]](#_bookmark216) to translate front view images into bird view images, then solve the detection problem by decomposing it into three subtasks of pedestrian localization, scale prediction, and classification. It achieves an outstanding performance of 6.37 Miss Rate (MR) on Caltech (reasonable) and 9.3 MR on CityPersons (reasonable) datasets.

We listed some recent works for pedestrian detection in Table [8.](#_bookmark21) These methods for pedestrian detection are often evaluated on Caltech [[163]](#_bookmark217) and CityPersons [[163]](#_bookmark217) datasets, which both include person-to-person occlusion caused by crowding and other objects. It is notable that these two datasets are designed specifically for pedestrian detection. A more complicated scenario of detecting vehicles and pedestrians simultaneously, is often validated using auto-driving datasets, such as KITTI [[164]](#_bookmark218) (see Table [18).](#_bookmark46) It is noteworthy that some handcrafted features, such as optical flow

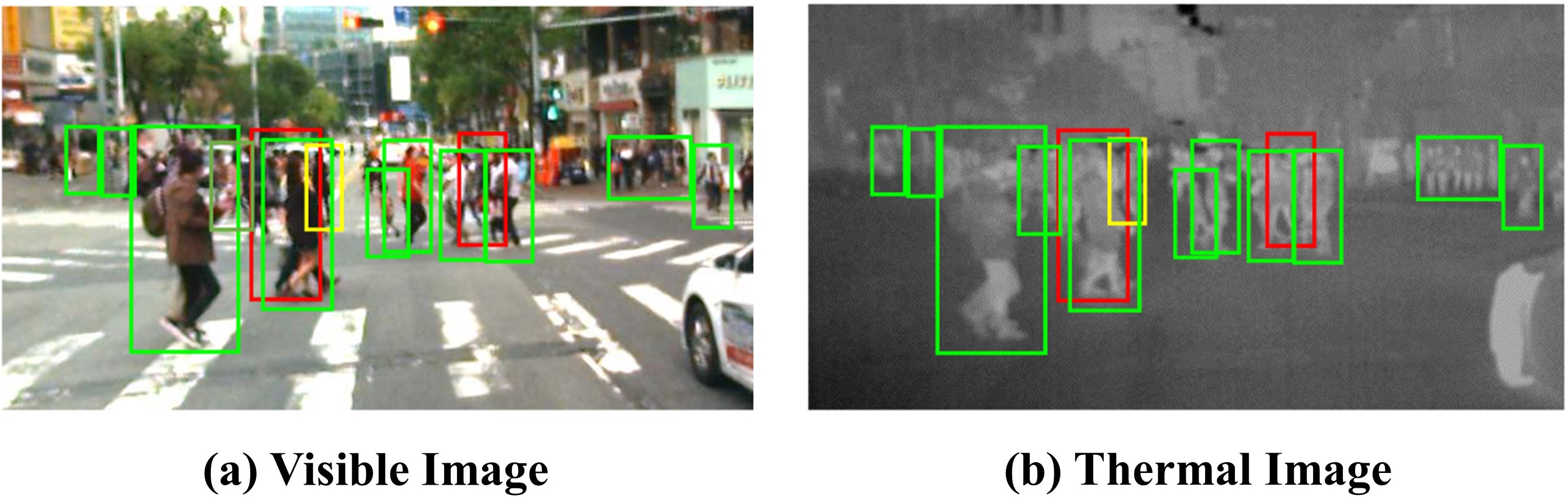


Figure 9: A dual feel camera feed (visible and thermal image pair) for multi-spectral pedestrian detection. Images are from [[165].](#_bookmark219)

features, are complementary to deep convolutional features, which can further boost the models’ ability [[166].](#_bookmark220)

Another interesting problem is pedestrian detection from multi-spectral images (such as RGB true-color + thermal camera feeds, as shown in Fig. [9.](#_bookmark19) This approach can be advantageous because infrared images provide more in- formative and robust features under low illuminations and extreme weather conditions. These works often require *feature fusion* to boost the overall performance. Feature fusion can be implemented in different stages, ranging from low-level (near the input layer) to high-level (near the output layer). The authors of [[167]](#_bookmark221) have shown that fusion at the middle-level (the authors name it *halfway fusion*) often achieves the best results. More recently, attention mech- anisms, including channel attention and semantic attention, are applied for feature fusion [[168]](#_bookmark222) to allow the network automatically learn the importance of different features. Alternatively, an illumination-aware weighting mechanism is used in [[169]](#_bookmark223) to learn the variation of illumination and adaptively mix the features of the visible (RGB) and thermal images. Some minor issues such as modality imbalance and weak alignment between different channels should be taken care of when fusing multiple camera feeds [[170,](#_bookmark224) [171].](#_bookmark225) A summary of recent implementations is presented in Table [8.](#_bookmark21) KAIST [[165]](#_bookmark219) and CVC-14 [[172]](#_bookmark226) datasets are often used as the benchmark validation dataset for these works. More datasets for pedestrian detection are provided in Table. [18.](#_bookmark46)

Table 7: Examples of object detection tasks for traffic analysis. If the dataset is not indicated, it means the current work uses the dataset generated by its authors. ’ means that this work uses fine-grained detection problem. ’\*’ Means this work is based on YOLOv5. It is worth mentioning that YOLOv5 may not be considered as a member of YOLO family.

6

YOLO family

SSD

CNN CNN

[[181]](#_bookmark235)Kim, et al.(2019)

1. Kasper-Eulaers et al.(2021)\*

|  |  |
| --- | --- |
| **Task Methods Paper: [Ref] Authors (year)** | **Performance: Accuracy [Dataset]** |
| [[173]](#_bookmark227)Espinosa, et al.(2017) | 70% |
| [[174]](#_bookmark228)Wang, et al.(2017) | 84.43% on DETRAC dataset [[179]](#_bookmark233) |
| Vehicle Detection R-CNN family [[175]Soin,](#_bookmark229) et al.(2017) | 100% |
| [[176]](#_bookmark230)Zhang, et al.(2017) | 96.5% |
| [[177]](#_bookmark231)Peppa, et al.(2018) | 97% |
| [[178]](#_bookmark232)Yu et al. (2017)6 | 98% |
| [[180]](#_bookmark234)Sang, et al.(2018)6 | 99.51%  85.29%on UA-DETRA[C[179]](#_bookmark233) |

1. Nayak et al.(2019)6
2. Zhang, et al.(2019) [[185]Chen,](#_bookmark239) et al.(2020) [[186]Cao,](#_bookmark240) et al.(2020) [[177]Peppa,](#_bookmark231) et al.(2018)

[[146]](#_bookmark200)Chen, et al.(2014) [[187]Zhou](#_bookmark241) et al.(2016)6

93% car, 63% truck front, 52% truck back (winter condition) 99.73%

77.94% mAP on UA-DETRA[C[179]](#_bookmark233)

84.5%on KITTI

92.18% on KITTI

98.2%

99.7%

62.85% on UTS(self), 64.44% PASCAL V[OC2007[188],](#_bookmark242) and 79.41% on LISA [2010[189]](#_bookmark243)

Plate Detection R-CNN family [[190]Lee,](#_bookmark244) et al.(2016) 99.94%

Traffic Sign Detection

YOLO family

SSD CNN

Pre-pocessing+CNN CNN

R-CNN family

YOLO family

[[191]](#_bookmark245)Kessentini, et al.(2019) [[192]Khazaee,](#_bookmark246) et al.(2020) [[193]Xie,](#_bookmark247) et al.(2018) [[194]Chen,](#_bookmark248) et al.(2019)

[[197]](#_bookmark251)Rene, et al.(2020) [[198]Hu,](#_bookmark252) et al.(2020)

[[199]](#_bookmark253)Danilenko, et al.(2020)

[[148]](#_bookmark202)Kim, et al.(2017) [[149]Selmi,](#_bookmark203) et al.(2017) [[150]Masood,](#_bookmark204) et al.(2017)

[[202]](#_bookmark256)Qian, et al.(2016) [[203]Shao,](#_bookmark257) et al.(2019) [[204]Zhang,](#_bookmark258) et al.(2020) [[205]Zuo,](#_bookmark259) et al.(2017) [[206]W](#_bookmark260)u, et al.(2019)

[[207]](#_bookmark261)Peng, et al.(2016)

[[209]](#_bookmark263)Zhang, et al.(2017) [[210]T](#_bookmark264)ai, et al.(2020) [[211]Liu](#_bookmark265) et al.(2021)\*

[[212]](#_bookmark266) Qin et al.(2021)\*

97.67% on GAP-LP [dataset[195]](#_bookmark249) 91.46% on Radar 97.9%

98.32% on UCSD 97.38% on [PKU[196]](#_bookmark250)

98.22% on AOLP

92%

90.12%

94+%

98.39% on [Caltech[200]](#_bookmark254)

94.8% on [Caltech[200]](#_bookmark254)

99.09% on [US[201]](#_bookmark255) 99.64% on [EU[201]](#_bookmark255)

85.58%

69.56% on [GTSDB+CTSD[208]](#_bookmark262)

98.7% on GTSDB

34.49% mAP on CCF2016 mAP 91.75% GTSDB mAP 90% on GTSDB

96.69% on CTSD and GTSDB

99.1% mAP

97.2% mAP

94.3 % mAP

[[213]](#_bookmark267)Gao, et al.(2019) [[214]Y](#_bookmark268)ou, et al.(2020)

SSD

91.0% on GTSDB 75% on TT100K

MSER+SVM+CNN

FullyConv CNN CNN

[[208]](#_bookmark262)Yang, et al.(2015) [[215]Zhu,](#_bookmark269) et al.(2016) [[216]W](#_bookmark270)u, et al.(2013)

[[217]](#_bookmark271)Shustanov, et al.(2017)

98.24% GTSDB 98.77% CTSD

91% TT100K

AUC 99.73% “danger” , 97.62% "mandatory" on GTSDB 99.94% on GTSDB

Table 8: Examples of pedestrian detection methods with their miss rate.

**Task Method Paper: [Ref] Authors (year) Performance: Accuracy [Dataset**

Faster R-CNN [[152]](#_bookmark206) Cai et al. (2016) 10% MR on Caltech

Fast R-CNN [[153]](#_bookmark207) Li et al. (2017) 9.32% MR on Caltech

CNN+Attention [[154]](#_bookmark208) Lin et al. (2018) 7.84% MR on Caltech

Faster R-CNN [[218]](#_bookmark272) Zhang et al. (2018) 4.1% MR on Caltech;11% MR on CityPersons;

Single-spectral

Multi-spectral

CNN+LSTM [[158]](#_bookmark212) Wang et al. (2018) 8.4% MR on Caltech

FCN [[159]](#_bookmark213) (2019) 3.8% MR on Caltech; 11.4% MR on CityPersons

Faster R-CNN+ Attention [[155]](#_bookmark209) (2019) 6.27% MR on Caltech;

Cycle-GAN [[161]](#_bookmark215) (2020) 6.37%MR on Caltech; 9.3% MR on CityPersons CNN+GCN [[157]](#_bookmark211) Xie et al. (2021) 6.4% MR on Caltech; 9.3% MR on CityPerson FCN+pattern-parameter matching [[219]](#_bookmark273) et al. (2021) 3.3% MR on Caltech; 10.4% MR on CityPersons

Faster R-CNN+ Fusion [[167]](#_bookmark221) Liu et al. (2016) 25.73% MR on KAIST Faster R-CNN+ Fusion [[169]](#_bookmark223) Li et al. (2019) 15.73% MR on KAIST CNN+ ATT+ Fusion IATDNN[34] [[220]](#_bookmark274) Guan et al. (2019) 14.93% MR on KAIST

CNN+Attention+ Fusion [[168]](#_bookmark222) Zhang et al. (2019) 14.12% MR on KAIST Faster R-CNN+ Fusion [AR-CNN[35][171]](#_bookmark225) Zhang et al. (2019) 9.34% MR on KAIST SSD+ATT+ Fusion MBNet [20[170]](#_bookmark224) Zhou et al. (2020) 8.13% MR on KAIST

CNN+memeory learning [[221]](#_bookmark275) Kim et al. (2021) 8.26% MR on KAIST; 23% MR on CVC-14 CNN+ATT+Fusion [[222]](#_bookmark276) Kim et al. (2021) 7.89% MR on KAIST; 18.7% MR on CVC-14 YOLOv5+ATT [[223]](#_bookmark277) Jiang et al. (2022) 7.85% MR on KAIST

Table 9: Evaluation metrics for different vision-based traffic analysis tasks (detection, classification, etc.)

**Metric Definition**

Correct predictions Total predictions

Accuracy

Recall (R) *T P*

*TP* +*FN*

Precision (P) *T P*

*TP* +*FP*

F1 score 2 × *P* ×*R*

*P* +*R*

(\*)

Pixel Accuracy (PA)  *T P* +*T N*

*TP* +*FN*

*TP* +*TN* +*FP* +*FN*

Miss Rate (MR) *F N*

Normalized error=|*d*−*dgt*| .

*gt*

*d*

Normalized error (mean)

*d* is the calculated distance and

*dgt* is the ground truth of distance.

J

Average Precision (AP) *AP* = 1 *P* (*R*)*dR* P-R CURVE (for one class)

0

mean Average Precision (mAP) *mean*(*APi*)

*Bp*∩*Bgt*

∪

Intersection over Union (IoU)

*Bp Bgt*

*Bgt*: ground truth bounding box

*Bp*: predicted bounding box

Disparity accurac[y[224]](#_bookmark278) *disparityinlier*%. The disparity ≤ 3px/5% is true

Stixel-wise percentage accuracy Similar to PA

*T*

2*ID*:*TP* +*ID*:*FP* +*ID*:*FN*

Φ denotes the number of fragmentations

Identification F1-Score (*ID* : *F* 1) *ID* : *F* 1 =  2*ID*:*T P*

multiple object tracking accuracy (MOTA) *MOTA* = 1 − *FN* +*FP* +Φ

2*PR Mw Mh*

*MCTA* = *P* + *R* (1 − *Tw* ) (1 − *Th* )

Multi-camera Tracking Accuracy (MCTA) *w*

*M*

*F* 1

: within-camera identity mismatches

within c amera han d over

*Tw*: true within-camera detections

*Mh*: handover mismatches

*Th*: true handover detections

*i*=1

RMSE *RMSE* = *N* (*yi* − *y*ˆ*i*)2*/N*

## Visual Tracking

Visual tracking refers to capturing the movement of specific objects by processing video frames. Traffic video process- ing by autonomous vehicles or traffic monitoring systems is perhaps the most popular application of visual tracking. With the advent of AVs and technology-assisted driving systems, this research area has become a hot topic. The main- stream algorithms can roughly be categorized into Correlation Filter-based Trackers (CFT) and non-CFT methods [[225].](#_bookmark279) The two challenging issues are the natural difficulty of reliable visual tracking and the lack of well-annotated datasets, especially for driving safety analysis.

Visual tracking methods can be categorized into discriminative methods [[226,](#_bookmark280) [227,](#_bookmark281) [228,](#_bookmark282) [229]](#_bookmark283) and generative meth- ods [[230,](#_bookmark284) [231,](#_bookmark285) [232,](#_bookmark286) [233,](#_bookmark287) [234]](#_bookmark288) from the modeling standpoint. Generative tracking methods comprise the following sequential steps: (i) extract the target features to learn the appearance model, which represents the target, (ii) search through the image area to find areas that best match the model, using pattern matching. The target information carried by generative models is often richer than that of the discriminative methods. Also, generative models make it is easier to meet the evaluation criteria and the real-time requirements of target tracking when processing a massive amount of data. The key components of generative methods include target representation and target modeling. The limitations of this approach include (i) background information of the image is not fully utilized, and (ii) the appearance of the target in different video frames may include substantial randomness and diversity, which affects the stability of the model.

Discriminative methods turn the tracking problem into a classification problem, and rely on training a classifier to distinguish between the target and the background. The target area is considered the positive sample in the current frame, and the background area is the negative sample. Discriminative methods turn the tracking problem into a classification problem, which can simultaneously utilize the information from the target and background. ML methods can be employed to train a binary classifier to distinguish between the target (considered as the positive sample) and the

background (considered as the negative samples), and can be updated online as more video frames are accumulated. The trained classifier is used to find the optimal area in the next frame. Discriminative methods are often more robust than generative models when facing appearance and environmental changes.

Correlation Filter (CF) methods and DL methods are often considered discriminant methods. In recent years, tracking methods based on correlation filtering [[235,](#_bookmark289) [236,](#_bookmark290) [237,](#_bookmark291) [238,](#_bookmark292) [239,](#_bookmark293) [240]](#_bookmark294) have gained a lot of attention from computer vision researchers because of their fast speed and reasonable performance.

The correlation filter is initialized by the given target in the first frame of the input. A classifier is trained by regressing the input features to the target Gaussian distribution. The response peak in the predicted distribution is found in the follow-up tracking step to locate the target’s position. Correlation filtering methods, when combined with deep features and CNN architectures (e.g., R-CNN series [[241,](#_bookmark295) [242,](#_bookmark296) [243],](#_bookmark297) SSD-based methods [[244])](#_bookmark298) exhibit outstanding performances and hence have gradually become a dominant approach in this field.

In addition to CF-based trackers, some other DL frameworks, even without using correlation filters, can also achieve an excellent performance. More elegant methods, including [[245,](#_bookmark299) [246,](#_bookmark300) [247,](#_bookmark301) [248,](#_bookmark302) [249,](#_bookmark303) [250]](#_bookmark304) tried to directly employ sequential learning models such as Long Short Term Memory (LSTM) or Recurrent Neural Networks (RNN) in their network structures after CNN-based feature extractors to capture the temporal information of video frames that repre- sent object motions.

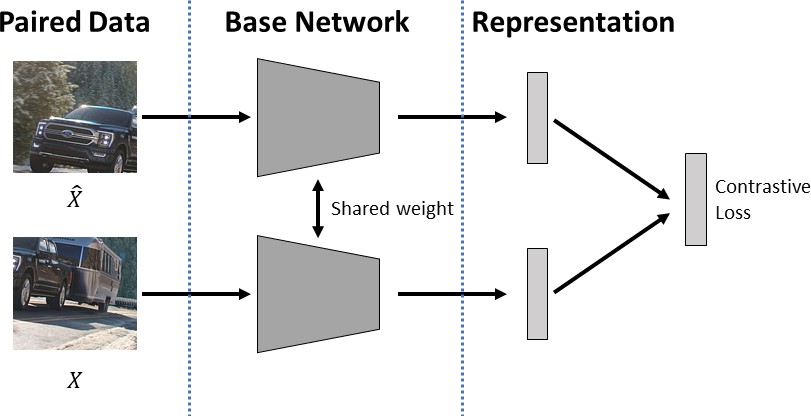


Figure 10: The architecture of basic Siamese neural network for similarity training.

Siamese Network structure (shown in Fig. [10)](#_bookmark24) offers a paradigm shift for visual tracking. The core idea of Siamese networks [[251,](#_bookmark305) [252,](#_bookmark306) [253,](#_bookmark307) [254,](#_bookmark308) [255,](#_bookmark309) [256,](#_bookmark310) [257]](#_bookmark311) is training twin networks to identify the similarity between two different images, such as the same object in consecutive video frames. These methods address both the similarity knowledge learning and the real-time operation requirements with acceptable tracking accuracy.

Many contemporary traffic monitoring systems still tend to use conventional tracking methods such as filtering and convolution methods due to their efficiency, low complexity, and stability. For examples, methods based on Kalman filtering [[258,](#_bookmark312) [259,](#_bookmark313) [260,](#_bookmark314) [261,](#_bookmark315) [262],](#_bookmark316) Gaussian Mixture Models (GMM) [[263,](#_bookmark317) [258],](#_bookmark312) Hidden Markov Models (HMM) [[264],](#_bookmark318) and SIFT-based [methods[265,](#_bookmark319) [266]](#_bookmark320) are used in traffic monitoring systems. However, using DL-based methods is gaining traction in recent years to perform traffic monitoring tasks due to the emergence of powerful and low-cost processing platforms, making DL methods more affordable and near real-time.

Hybrid methods that enable tracking by detection are another possibility. For instance, a DL method can be used for fast and accurate object detection, followed by a second estimator based on conventional methods, Kalman filtering, and Kanade–Lucas–Tomasi (KLT) feature tracker for tracking purposes. This approach simplifies the processing job for object detectors designed for specific tasks, such as multi-spectral pedestrian detection.

A summary of some important implementations is presented in Table [10.](#_bookmark25) Note that datasets KITTI, and MOT 15 Chal- lenges [[267]](#_bookmark321) include pedestrians, in addition to vehicles. Several studies, including [[268,](#_bookmark322) [269,](#_bookmark323) [270],](#_bookmark324) are specifically designed to improve the safety of humans.

Table 10: Some traffic-related visual tracking method that use deep learning. The default dataset is generated by the author of each work. The default performance metric is accuracy unless specified otherwise.

|  |  |  |
| --- | --- | --- |
| **Paper: [Ref] Authors (year)** | **Methods** | **Performance** |
| [[271]](#_bookmark325)Qiu, et al.(2018) | YOLO+KLT | 76.4% Recall 88.2% Precision |

[[272]](#_bookmark326)López-Sastre, et al.(2019) Faster R-CNN 30.5AP on subset:M-30 66.2%AP on subset:M-30-HD [[268]Scheide](#_bookmark322)gger, et al.(2018) CNN+PMBM [filter[273]](#_bookmark327) 80.04% MOTA on KITTI

38.1%AP on subset:Urban1 of GRAM-RTM

75.29% MOTA campus

[[269]](#_bookmark323)Zou, et al.(2019) Siamese network+SPP+MDP

76.06% MOTAurban

78.14% MOTA highway on KITTI

[[274]](#_bookmark328)Li, et al.(2019) FPN+tracking loss 83.2% IDF1 on nivida AI city

|  |  |  |
| --- | --- | --- |
| [[275]](#_bookmark329)Nikodem, et al.(2020) | hourglass | MOTA 97+%  MCTA 91+% |
| [[276]](#_bookmark330)zhao, et al.(2018) | SSD+dual Kalman filters | Shown in the form of figures |
| [[277]](#_bookmark331)Wang, et al.(2019) | YOLOv3+SIFT | 81.3% MOTA |
| [[278]](#_bookmark332)Usmankhujaev, et al.(2020) | yoloV3+kalman filter | 100% Daytime Wrong cases detection  89.83% Daytime(flipped) Wrong cases detection |
|  |  | 86.11% Nighttime(flipped) Wrong cases detection |
| [[279]](#_bookmark333)Kwan, et al.(2018) | ResNet | For compressive measurements |
| [[270]](#_bookmark324)Fernández-Sanjurjo,et al.(2019) | CNN detector+DCF+Kalman filter | 86.96% MOTA on MOT [15[267]](#_bookmark321) |

## Semantic Segmentation

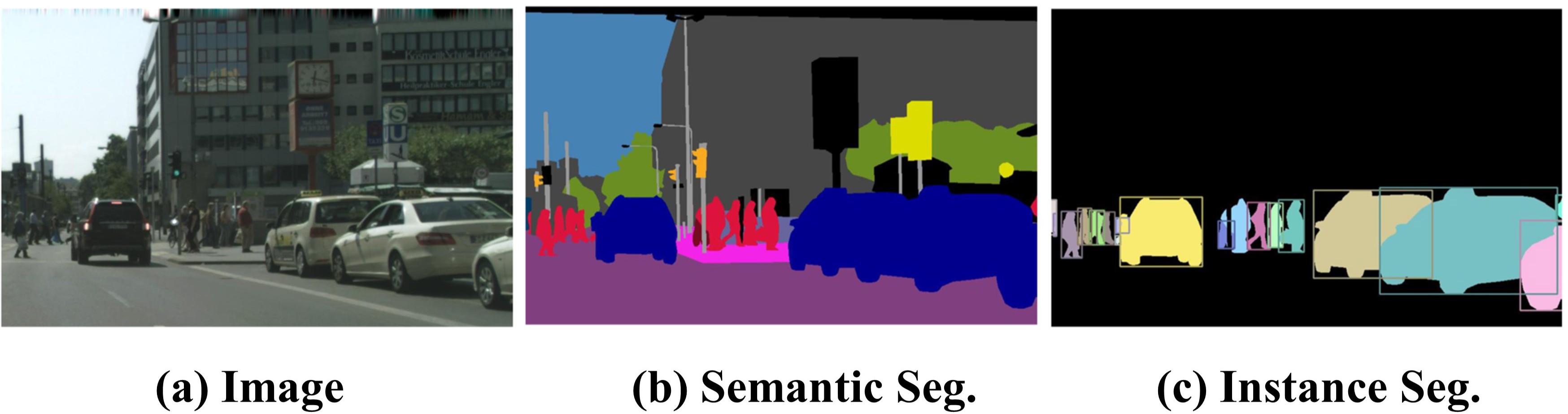


Figure 11: A example of different types of segmentation. Source from [[280].](#_bookmark334)

Semantic segmentation, where objects of different types are separated, can be considered the heart of many video pro- cessing tasks. For instance, vehicle detection, vehicle tracking, and environment perception in a crowded environment with interlaced and overlapping objects can be powered by semantic segmentation when regular segmentation meth- ods fail to separate objects from complex backgrounds. An example of semantic segmentation is shown in Fig. [11(b).](#_bookmark26) The purpose of semantic segmentation is to label each pixel of an image to represent different categories (e.g., cars, pedestrians, roadside infrastructures, traffic signs, etc.). For instance, semantic segmentation can be employed by an autonomous vehicle for background modeling, identifying road boundaries and free spaces, and detecting lane mark- ings and traffic signs. Semantic segmentation can also be used by an external traffic monitoring system for analyzing the behaviors of human-driven and self-driving vehicles in specific zones and times. To avoid reliance on massive data collection and expensive annotations, semi-supervised and weakly-supervised learning methods [[281,](#_bookmark335) [282,](#_bookmark336) [283,](#_bookmark337) [284]](#_bookmark338) are developed for low-cost implementation with reasonable performance.

Early works tended to deploy existing classification algorithms at the patch level for semantic segmentation. Since 2014, Fully Convolutional Network [(FCN)[285]](#_bookmark339) was introduced that allows spatially dense prediction tasks by trans- lating famous DL architectures such as AlexNet, VGG net, and GoogLeNet into fully convolutional network archi- tectures. Afterward, many upgraded architectures such as [U-net[286]](#_bookmark340) and Se[gNet[287]](#_bookmark341) were proposed, which build upon the concept of FCN and utilize auto-encoder architectures for semantic segmentation with small training datasets

using data augmentation methods. This architecture is further updated to multi-stage auto-encoder networks in [[288].](#_bookmark342) In some w[ork[289,](#_bookmark343) [290,](#_bookmark344) [291,](#_bookmark345) [292],](#_bookmark346) atrous/dilated convolution architectures are used to keep spatial resolution and expand the receptive fields. The authors of [[293]](#_bookmark347) expanded the receptive fields by employing large kernel with its proposed global convolution.

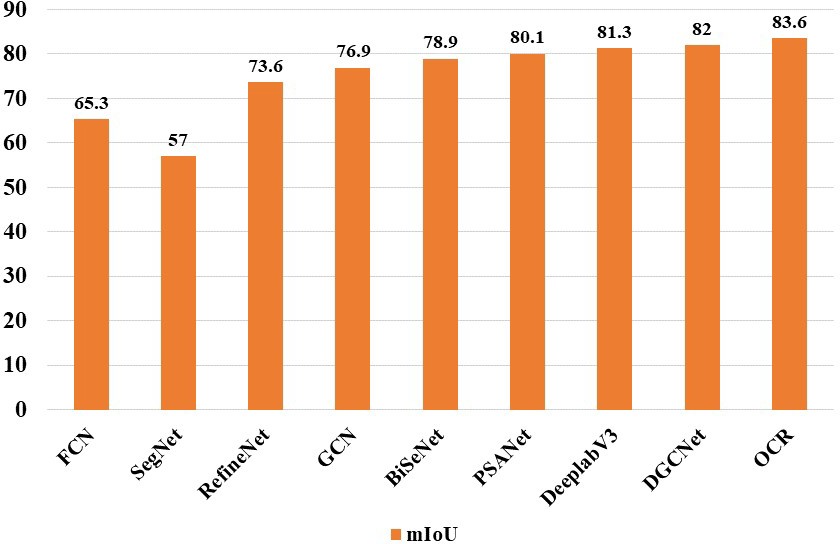


Figure 12: Semantic segmentation models perform on Cityscapes.

In [[294,](#_bookmark348) [295,](#_bookmark349) [296],](#_bookmark350) a feature fusion method is deployed that allows the framework to learn global features merged with more local features. For these methods, Conditional Random Fields can be used to enhance the output. Other works [[297,](#_bookmark351) [298]](#_bookmark352) are based on a Recurrent Neural Network (RNN) structure that can better tackle sequence-related tasks. Additional models [including[299]](#_bookmark353) based on graph convolutional network, [[300]](#_bookmark354) based on pyramid pooling model, and [[301]](#_bookmark355) based on learning relations between the object region and pixels have competitive performance. Furthermore, [[302,](#_bookmark356) [303,](#_bookmark357) [304]](#_bookmark358) focused on semantic segmentation with 3D point cloud data, which have great potentials for autonomous driving and traffic safety analysis. More specifically, the methods [[302,](#_bookmark356) [303]](#_bookmark357) are evaluated by indoor scene dataset, while [[304]](#_bookmark358) is evaluated by urban scene captured by scanners, something potentially more relevant for traffic analysis. The performance of some models is shown in Fig. [12.](#_bookmark27)

The applications of semantic segmentation frequently appear in the world of AVs. Some examples include (i) scene understanding, which involves understanding the traffic environment with road users, (ii) free space estimation to determine the available spaces on the road that a vehicle is allowed to use with no collisions, and (iii) Stixel repre- sentation, which assigns each pixel with a 3D depth information. A summary of related works is presented in Table [11.](#_bookmark28)

Table 11: Some semantic segmentation works in the traffic field.

|  |  |  |
| --- | --- | --- |
| **Task Paper: [Ref] Authors (year)** | **Methods** | **Performance** |
| [[305]](#_bookmark359)Romera, et al(2017) | Autoencoder | pixel accuracy*>*95% Cityscapes |
| [[306]](#_bookmark360)Lyu et al.(2019) | Edge Detection Network+Fusion | 63.2% mIoU Cityscapes |
| Scene understanding [[307]Deng,](#_bookmark361) et al.(2017) | CNN+pyramid pooling module | 54.5% mIoU Cityscapes |
| [[308]](#_bookmark362)Sáez, et al.(2018) | Autoencoder | 59.3% mIoU Cityscapes |
| [[309]](#_bookmark363)Kendall, et al. | Bayesian Autoencoder | 63.1% mIoU CamVid |
| [[310]](#_bookmark364)Ohgushi, et al.(2020) | Autoencoder | 21.9% mIoU |
| [[311]](#_bookmark365)Hua, et al.(2019) | Autoencoder+fusion+optical flow | Path planning accuracy |
|  |  | 0.15m Indoor and 0.27m Outdoor |
| Free space estimation [[312]Le](#_bookmark366)vi, et al.(2015) | CNN | 0.87 AUC |
|  |  | 89.12% maxF SEGMENTATION on KITTI |
| [[313]](#_bookmark367)Deepika, et al.(2017) | SegNet | 0.9667 IoU |
| Stixel representation [[314]Schneider](#_bookmark368), et al.(2016) | FCN+SGM | 7.8 Disparity Error on KITTI 15.2% on Ladicky |
| [[315]](#_bookmark369)Cordts, et al. (2017) | FCN+SGM+graphical model | 83.1% exact Disparity accuracy |

## Instance Segmentation

Instance segmentation, which deals with detecting and delineating distinct objects of interest in images and video frames, can be considered as one of the most difficult tasks in computer vision (Fig. [11(c))](#_bookmark26). It goes one step beyond semantic segmentation and not only labels the pixels based on their object categories, but also distinguishes between different object instances of the same type. This is of crucial importance for traffic imagery analysis in dense zones, where different objects (e.g., vehicles, pedestrians) have to be identified and located in video frames for optimal decision making by AVs, or to extract safety metrics by monitoring systems. In contrast to semantic segmentation, instance segmentation only needs to find the edge contour of the object of interest with no need for bounding boxes, hence it can realize a more accurate object detection when assessing the behaviors of vehicles. Building a reliable and real-time method, for instance, segmentation, especially for crowded zones and under highly distorted traffic videos (e.g., in rainy and cloudy weather conditions), can be challenging.

Instance segmentation can be divided into one-stage and two-stage methods. Two-stage methods often require gener- ating region or object proposals followed by a classification-based segmentation performed over the features extracted from the selected regions or bounding boxes around object proposals. To generate region proposal, [[316,](#_bookmark370) [317,](#_bookmark371) [109]](#_bookmark163) predict a bounding box for each instance, while [[318,](#_bookmark372) [295,](#_bookmark349) [319,](#_bookmark373) [320]](#_bookmark374) develop pixel-wise coarse segmentation masks.

Since instance segmentation partitions the image by masking the detected objects and associating each pixel with a distinct object, some two-stage detectors such as Faster R-CNN [[122])](#_bookmark176) can execute instance segmentation task after some post-processing, e.g., by adding a branch for mask predictions.

One-stage instance segmentation methods do not utilize a separate stage for generating region proposals; rather, they apply the segmentation directly to the original images. Some methods [[321,](#_bookmark375) [322,](#_bookmark376) [323,](#_bookmark377) [324]](#_bookmark378) inspired by one-stage detectors (such as Y[OLO[135])](#_bookmark189) directly predict bounding boxes. However, these anchor-based methods heavily rely on predefined anchors, which may be affected by many factors such as the predefined anchor boxes’ aspect ratio and scales. Another approach is developing anchor-free methods using dense prediction or centerpoint/keypoints. For instance, [[325,](#_bookmark379) [326,](#_bookmark380) [327]](#_bookmark381) relied on [FCOS[139]](#_bookmark193) as their dense prediction detector, while [ExtremeNet[145]](#_bookmark199) is a keypoint- based detector that can roughly perform the segmentation task. The difference between the accuracy of one-stage and two-stage methods is not as great as one may expect. Indeed, recent one-stage methods such as [CenterMask[326]](#_bookmark380) can perform real-time inference with accuracy as high as two-stage methods, or even better. The performance of some instance segmentation models is shown in [Fig.13.](#_bookmark29)

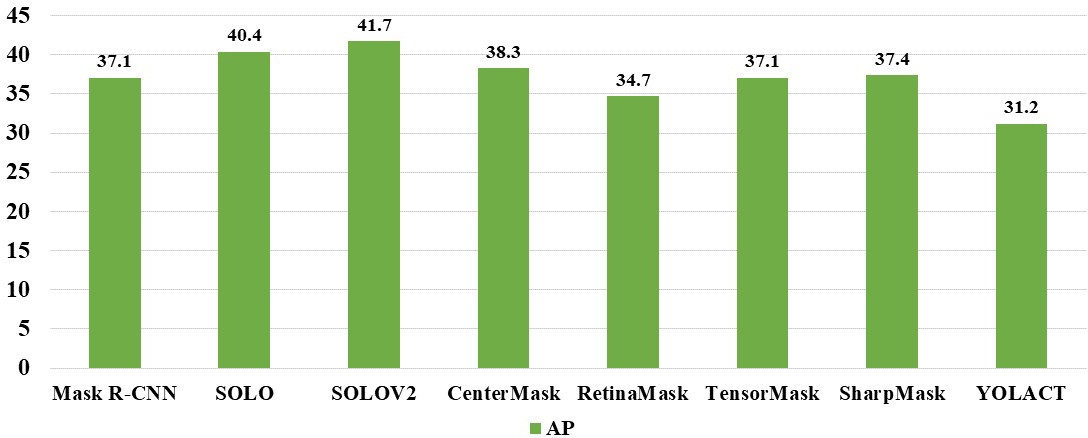


Figure 13: Instance segmentation models perform on MS COCO test-dev

In the context of traffic analysis, instance segmentation can be used not only to identify and locate vehicles but also to obtain detailed information about the vehicle, such as a vehicle’s class, number of axles, 3D bounding box, dimension, etc. It can be used as part of the processing to identify road lanes, traffic volume, etc. For instance, one may consider each lane as an instance. Some famous methods that utilize instance segmentation for traffic image analysis are presented in Table [12.](#_bookmark30)

Table 12: Some instance segmentation methods used for traffic imagery analysis. If the dataset is not indicated, it means that a proprietary dataset generated by the authors is used.

**Task [REF] authors (Year) Methods Performance**

Obtain comprehensive vehicle information

Lane detection

[[328]](#_bookmark382)Zhang, et al.(2015)

[[329]](#_bookmark383)Mou, et al.(2018) [[330]Zhang,](#_bookmark384) et al.(2020) [[331]Huang,](#_bookmark385) et al.(2018)

[[332]](#_bookmark386)Neven, et al.(2018) [[333]Roberts,](#_bookmark387) et al.(2018)

CNN+MRF

ResFCN Mask R-CNN Mask R-CNN

multi-task CNN SegNet

59.0% object recall,

83.1% of the randomly sampled foreground pixel pairs ordered on KITTI 95.87% F1 score on ISPRS

97% vehicle types accuracy

1.333 front 4.698 side-way KITTI

96.4% accruacy

IoU Mapillary 82.9% CityScapes 85.2%

KITTI 83.8% author’s dataset 95%

3D reconstruction [[334]Hadi,](#_bookmark388) et al.(2020) Mask R-CNN AP@50% 8.862% CityScapes 43.949%

[IDD[335]](#_bookmark389) 5.643% W[ildDash[336]](#_bookmark390)

## Video-based Event Recognition

Video-based event recognition extends the role of DL methods from object detection and identification paradigms into a more intricate problem of understanding events. It provides endless possibilities to explore the interactions among objects in an interactive environment rather than focusing on disjoint object-based tasks. Indeed, without event detection and analysis, the majority of video information remains unexploited and underutilized. Note that many safety metrics relate to the interactions of vehicles with one another and with the environment. For instance, traffic sign interpretation can be recast as an image-based object classification problem, while more intricate violations of traffic safety such as unsafe lane changing behavior without signaling require modeling interactions between vehicles and their surrounding environments. Such challenging problems are still in their infancy stages and apparently require heavy investment by the research community. In essence, the event recognition problem is also related to another well-investigated problem of video-based human action recognition, and similar tools and algorithms can be adopted here.

An alternative method of event analysis is using conventional analysis approaches by extracting object-based infor- mation and manually feeding them into statistical and reasoning models such as Hidden Markov Models (HMM) for safety analysis. However, with the recent advances in developing powerful DL methods, they enable a more auto- mated and direct way of evaluating the behaviors of involved vehicles. The most naive way of event recognition can be realized by extracting static features from video frames using methods like SIFT [[337],](#_bookmark391) SURF [[100],](#_bookmark154) the Local Binary Patterns (LBP) [[338,](#_bookmark392) [339],](#_bookmark393) HOG detector [[127],](#_bookmark181) Binary Robust Invariant Scalable Keypoints (BRISK) [[340],](#_bookmark394) Features from Accelerated Segment Test (FAST) [[341,](#_bookmark395) [342]](#_bookmark396) and GIST (a very low-dimensional scene representation) [[343,](#_bookmark397) [344],](#_bookmark398) and then performing object detection followed by a time-series analysis for even recognition. Some other methods combine the feature extraction and time-series analysis stage into directly extracting temporal features using methods like motion spatio-temporal features (Motion SIFT (MoSIFT) [[345],](#_bookmark399) Spatio-Temporal Interest Points (STIP) [[346],](#_bookmark400) and Dense trajectories [[347,](#_bookmark401) [348]),](#_bookmark402) then perform the classification task.

More contemporary event detection algorithms benefit from DL methods to automate this process, and a dominant method is directly applying a 3D convolutional network to process non-anomalous frames [[349].](#_bookmark403) Another approach is deploying CNN to extract spatial features and then performing sequential analysis using methods such as RNN/LSTM [[350,](#_bookmark404) [351,](#_bookmark405) [352,](#_bookmark406) [353,](#_bookmark407) [354,](#_bookmark408) [355,](#_bookmark409) [356]](#_bookmark410) to preserve the temporal features.

Most of these methods use supervised learning methods to detect a set of predefined events. Therefore, developing generic methods for understanding safety risks from driving profiles and tackling unseen types of safety violations has a long way ahead.

Event recognition is of particular importance for traffic safety analysis since it can be used for detecting abnormal events and traffic violations and their associations with crash rates [[357],](#_bookmark411) car behavior analysis [[358,](#_bookmark412) [359],](#_bookmark413) and pedes- trians’ crossing identification [[360,](#_bookmark414) [354,](#_bookmark408) [361].](#_bookmark415) Recently, some w[orks[362,](#_bookmark416) [363,](#_bookmark417) [364]](#_bookmark418) try to predict anomaly actions using Generative Adversarial Networks (GAN). The core idea is predicting the future video frames for a normal user with rational behavior from the history of normal sequences to identify severe abnormalities by comparing the observed video frame against the anticipated one.

For vehicle-level analysis, when the goal is detecting plain and simple events, conventional methods achieve a reason- able performance. For instance, [[365]](#_bookmark419) uses HMM to detect traffic abnormality, and [[366]](#_bookmark420) deployed a topic model to recognize crashes from surveillance videos. However, using DL methods can be used to analyze more complex events and achieve higher performance records. Some generic platforms like Rekall [[367],](#_bookmark421) provide a query-based approach to translate the challenging task of event recognition into a sequence of object detection and classification problems.

We summarize important DL-based event recognition methods in Table [13,](#_bookmark31) and present some popular datasets for event recognition tasks in Table [18.](#_bookmark46) One observation is that unsupervised, semi-supervised, and self-supervised models are becoming more prevalent in recent works [[357,](#_bookmark411) [368](#_bookmark422), [364]](#_bookmark418) to mitigate the costly and tedious job of video annotation and simplifies volume video processing.

Table 13: Some recent DL works for video-based traffic abnormal event detection. Unless otherwise specified, the non-indicated numbers is the accuracy.

|  |  |  |
| --- | --- | --- |
| **Paper: [Ref] Authors (year)** | **Methods** | **Performance** |
| [[364]](#_bookmark418)Nguyen, et al.(2020) | GAN | F1 score 0.9412 AI City Challenge 2019 |
| [[368]](#_bookmark422)Yao, et al.(2019) Auto Encoder-Decoder 60.1% AUC on A3D Dataset | | |
|  | with GRU |  |
| [[369]](#_bookmark423)Tian, et al.(2019) | YOLO-CA | 90.02% AP CAD-CVIS |
| [[370]](#_bookmark424)Kim, et al.(2020) | 3D conv | 82% |
| [[371]](#_bookmark425)Ijjina, et al.(2019) | 3D conv | 71% |
| [[372]](#_bookmark426)Shah, et al.(2018) | [DSA-RNN[373]](#_bookmark427)  Faster R-CNN | 47.25% on CADP |
| [[374]](#_bookmark428)Srinivasan, et al.(2020) | Detection T[ransformer[375]](#_bookmark429) | 78.2% on CADP |
| [[376]](#_bookmark430)Suzuki, et al.(2018) | [QRNN+DeCAF[377]](#_bookmark431) | 99.1% mAP |
| [[357]](#_bookmark411)Giannakeris, et al.(2018) | Faster RCNN | F1-score 0.33 RMSE 227 on NVIDIA CITY Track 2 |
| [[378]](#_bookmark432)Arceda, et al.(2018) | YOLO+V[iF[379]+SVM](#_bookmark433) | 89% |
| [[380]](#_bookmark434)Biradar, et al.(2019) | YOLOv2+ CNN | F1-score 0.3838 RMSE 93.61 on NVDIA CITY Track 3 |
| [[381]](#_bookmark435)Xu, et al.(2018) | Mask-RCNN+ ResCNN | F1-score 0.8649 RMSE 3.6152 on NVIDIA CITY Track 2 |
| [[382]](#_bookmark436)Doshi, et al.(2020) | YOLO+KNN+K-means | F1-score 0.5926 RMSE 8.2386 on NVIDIA CITY track 4 |
| [[358]](#_bookmark412)Zhou, et al.(2016) | 3D Conv | 95.2% on U-turn dataset |
| [[359]](#_bookmark413)Franklin, et al.(2020) | YOLOv3 | 100% and 95.34% for input video 1 and video 2 |

These pure data-driven methods often focus on detection problems. Alternatively, other automated video-based road safety analysis frameworks exist that use ML/DL methods to extract information about the road users from RSU videos and perform safety analysis using domain knowledge. An important class of such studies is extracting surro- gate safety measures. For example, the authors of [[383]](#_bookmark437) collected large-scale data in about 40 roundabout weaving zones. They track the vehicles using the Kanade–Lucas–Tomasi (KLT)-based tracker [[384],](#_bookmark438) then extract a set of sur- rogate measures, such as speed, individual interaction measurements, and Time-To-Collision (TTC), for each vehicle. Performing correlation analysis between the surrogate measures and complementary data (such as design geometry and environment attributes) reveals insightful relations about traffic safety. We also note that [[385,](#_bookmark439) [386]](#_bookmark440) focus on the analysis of pedestrian-vehicle interactions by studying the secondary interaction and collision risk predictions. These works are worthy of high attention. Although these sorts of analyses require extracting more complicated patterns from traffic videos, they can be helpful for enhancing the real-world traffic safety. A summary of such frameworks is presented in Table [14.](#_bookmark32) We note that most of these frameworks use conventional tracking algorithms, which yield reasonable performance. However, more advanced hybrid detection and tracking algorithms can be developed where DL networks are used for fast and accurate object detection, followed by a second estimator based on the conventional methods, as discussed at the end of Section [5.3).](#_bookmark23) For instance, one may combine YOLOv5 and DeepSort [[243]](#_bookmark297) for precise vehicle tracking [[387]](#_bookmark441).

## Sensor Information Processing

It is notable that there are several studies and datasets devoted to sensor information analysis. Different types of commonly used sensors were provided previously in section [3.](#_bookmark9) Of particular and increasing interest is the point cloud mapping collected from LiDARs, not just because they offer more accurate distance measurement, but also they are considered as separate and independent sensing of the environment to that of videos to ensure accurate perception thus road safety. 3D point cloud mapping from LiDAR is different from grid-based 2D images, thus different treatment strategies are pursued. LiDAR point cloud semantic segmentation works use deep neural networks, initially treating point cloud as construct graph [[399],](#_bookmark453) followed by the development of multi-layer perceptrons to learn from raw cloud data directly [[302,](#_bookmark356) [303].](#_bookmark357) More recently, the spherical projection has been employed to map LiDAR sequential scans to depth images, and improved segmentation [[400,](#_bookmark454) [401,](#_bookmark455) [402,](#_bookmark456) [403].](#_bookmark457) Since the focus of this paper is video-processing for traffic safety analysis, we refer the interested readers to [[404,](#_bookmark458) [405,](#_bookmark459) [406,](#_bookmark460) [407].](#_bookmark461)

Table 14: Automated video-based road safety analysis frameworks.

**REF] authors (Year) Video Process**

**Method**

**Analysis Method**

**Description**

[[383]](#_bookmark437) St-Aubin et al. (2015) KLT Dataset Collection

KLT for tracking;

[[388]](#_bookmark442) Zangenehpour et al. (2016)

Bayesian classification for se[g.[389];](#_bookmark443)

Regression Analysis; Rank correlation analysis;

Cyclist and motor-vehicle interactions

1. Lu et al. (2016) KLT Sensitivity analysis;

Golden section search

Calibrate car-following parameters in VISSIM simulation;

1. Mohamed et al. (2018)

KLT;

Kinematic method

Motion pattern matching (MPM) by

the longest common sub-sequence (LCSS)

Distribution/frequency analysis; Clustering

Study on impact of motion prediction methods on safety indicators

1. Xu et al. (2018) YOLOv2;

NMS

1. Battiato et al. (2018) Kernel-based object tracking [[394];](#_bookmark448)

HOG

Database building for pedestrian analysis

Bayesian classification Risk analysis from on-board video data

[[385]](#_bookmark439) Fu et al. (2019) BriskLUMINA 0.1 [[395]](#_bookmark449) Statistic Analysis;

Correlation analysis

Secondary Pedestrian-vehicle interactions

1. Xie et al. (2019)
2. Chen et al. (2020)

KLT; rPCA;

Dirichlet process Gaussian mixture model (DPGMM)

HOG;

SVM;

Kalman Filter;

Adaptive Gaussian Mixture model

HMM model the rear-end conflicts

Distribution analysis Safety space analysis;

Data collected by UAV

1. Yang et al. (2021) KLT;

Kalman Filter

1. Noh et al. (2022) Mask R-CNN; YOLOv5;

DeepSort

Functional Data Analysis Anomalies detection;

LSTM Pedestrian-vehicle collision risk prediction Regression Analysis;

Data collected by UAV

1. Chen et al. (2022)

DeepSort

Rank correlation analysis;

Coalition game theory

Traffic risk analysis

## Network-level Analysis

Traffic flow problems can be formulated as a network of mobile nodes, and studies on individual crash analysis can be extended to the more complex setup of network-level analysis.

There exist a few research paradigms that consider network-level analysis. One bold example is the transportation network design and related family of problems. Transportation network design belongs to the category of operations research and can be divided into the Road Network Design Problem (RNDP) and Service Network Design Problem (SNDP) according to their features and [functions[408].](#_bookmark462) The works [[409,](#_bookmark463) [410,](#_bookmark464) [411]](#_bookmark465) of RNDP aim to optimize the performance of urban networks according to some criteria such as topology, capacities, and flow accessibility. The works [[412,](#_bookmark466) [413,](#_bookmark467) [414,](#_bookmark468) [415,](#_bookmark469) [416]](#_bookmark470) of SNDP aim to address the planning of operations for freight transportation carriers, such as station locations, route planning, and operation frequency.

Traffic prediction studies often employ statistical techniques (such as Kalman filtering [[417],](#_bookmark471) hidden Markov model [[418],](#_bookmark472) Bayesian interference [[419])](#_bookmark473) and DL (such as LSTM, CNN) methods [[420,](#_bookmark474) [421,](#_bookmark475) [422,](#_bookmark476) [423]](#_bookmark477) to infer the network state and produce optimal strategies for different conditions.

Network-level analysis can be used for traffic safety analysis as well. Some key objectives would include finding correlations between traffic flow, safety metrics geo-maps, and crash rates. For example, one may expect a direct relation between the traffic composition (density and variety of vehicles) and the number of crashes at different parts of highways. One may also expect relations between the traffic flow and crash rates of nearby intersections or segments. Network-level analysis can shed light on these highly unexplored research areas.

There exist four general approaches for network-level analysis [[424]](#_bookmark478) including traditional statistical models (e.g., [[425]),](#_bookmark479) endogeneity/heterogeneity models (e.g., [[426,](#_bookmark480) [427]),](#_bookmark481) data-driven methods [[428,](#_bookmark482) [429],](#_bookmark483) and causal inference models. Furthermore, we note that some [models[430,](#_bookmark484) [431]](#_bookmark485) exploit previously collected crash data with road in- formation (such as Average Daily Traffic (ADT), lane width, speed limited, shoulder width) to estimate crash fre- quencies at intersections or segments. Some models [[432,](#_bookmark486) [433]](#_bookmark487) explore risk probabilities by processing geometric features. Recently, new [models[434,](#_bookmark488) [435,](#_bookmark489) [436,](#_bookmark490) [437,](#_bookmark491) [438,](#_bookmark492) [439]](#_bookmark493) take advantage of advanced sensors techniques and high-performance computation frameworks to infer real-time crash risks and take proactive strategies. Safety anal- ysis frameworks can perform integrative analysis by incorporating different static and dynamic data modalities (i.e., imagery and sensor inputs) from different points of view to comprehend the network status and derive realistic distribu- tions for safety factors. An immediate benefit of such networks would be assessing the contribution of different factors on safety distributions and providing advisory to improve roadways and infrastructure design as well as developing safety enforcement and public education campaigns.

A key challenge is developing strategies and scheduling policies for data aggregation to provide required modalities for network-level safety analysis at the minimum cost possible. Also, data aggregation is constrained by the utilized networking infrastructure and communication protocols between the vehicles and roadside infrastructure. Study of such networks are out of the scope of this work, and we refer the interested users to [[440,](#_bookmark494) [441,](#_bookmark495) [442,](#_bookmark496) [443,](#_bookmark497) [444,](#_bookmark498) [429,](#_bookmark483) [445,](#_bookmark499) [446,](#_bookmark500) [440]](#_bookmark494)

Recently, the ideas of using data augmentation and physics-informed neural networks (PINN) are proposed to mimic the dynamics of complex systems while mitigating the need for manual annotation of massive datasets. We believe that the power of PINN and data augmentation is not yet fully utilized in this context. There is a great potential to develop surrogate models for traffic flow and risk analysis. The authors also believe that elegantly designed graph neural networks can play an essential role in modeling network-level events and trends.

# Sample Problems

Safety assessment is a qualitative process, which can be approached by a set of specific and objective sub-problems. For instance, the overall safety of a highway section can be assessed by a set of exemplary problems provided in Table

[15.](#_bookmark34) Cloud-based software can process videos captured by the roadside infrastructure to extract statistical information from the observed events. The results of such analyses can be used to evaluate the highway’s safety profile and offer revisions to the traffic management guidelines to the transportation personnel. For instance, frequent roadblocks in specific sections of a highway may require widening the road, revisiting speed limits, prohibiting commercial vehicles, or planning traffic re-routing.

Table [15](#_bookmark34) presents typical processing steps required for each sample problem. As we discussed in this paper, some technical papers offer a solution for some problems, while more work is required to solve some other problems. Also, it is worth mentioning that some steps are necessary for each problem, while some other pre-processing steps such as denoising and video stabilization may or may not be included to balance between the accuracy and complexity.

Table 15: List of sample problems to assess the overall safety of a highway segment. The short codes include VS: video stabilization, DN: denosing, SR: super resolution, MOT: multi-object tracking, OD: object detection, IS: instance segmentation, TE: trajectory extraction, SS: semantic segmentation, C: classification. The step in brackets "()" denotes this step is not required but potentially can enhance the performance. The tasks with ’\*’ meaning that these tasks can be solved by obtaining the relationships (distance, velocity) among vehicles and determining a threshold from the relationships.

|  |  |  |
| --- | --- | --- |
| **Event** | **Processing Steps** | **Examples** |
| Vehicle Stopped on Shoulder | (VS)-(DN)-LD-MOT | [[381]](#_bookmark435) |
| Car Crash | (VS)-(DN)-OD/MOT-(IS)-C | [[369,](#_bookmark423) [364]](#_bookmark418) |
| Emergency Vehicle on The Road | (VS)-(DN)-fine-grained OD | [[183]](#_bookmark237) |
| Careless/Evasive Lane Change | (VS)-(DN)-LD-MOT-TE-(smooting)-C | [[447,](#_bookmark501) [448]](#_bookmark502) |
| Debris in Roadway | (VS)-(DN)-LD-(SR)-OD/(SS) | [[310,](#_bookmark364) [311,](#_bookmark365) [313]](#_bookmark367) |
| Traffic Blocked (Slowed-down) | (VS)-(DN)-MOT-(smoothing)-TE-(SE) | [[449,](#_bookmark503) [450]](#_bookmark504) |
| Sharp Braking | (VS)-(DN)-MOT-(smoothing)-TE | [[451]](#_bookmark505) |
| Passing Red Traffic Light | (VS)-(DN)-(OD for ligthts)-MOT | [[452]](#_bookmark506) |
| Traffic Composition | (VS)-(DN)-OD/MOT | [[453]](#_bookmark507) |
| \*Vehicle Driving Obviously Excessively Slow | (VS)-(DN)-MOT-TE-(smoothing) | - |
| \*Vehicle Driving Obviously Excessively Fast | (VS)-(DN)-MOT-TE-(smoothing) | - |
| Vehicle Driving in the Prohibited Area | (VS)-(DN)-LD-OD | [[454]](#_bookmark508) |
| Invalid Car in HOV | (VS)-(DN)-LD-OD | - |
| Improper (Careless) Entering the Road | (VS)-(DN)-LD-MOT-TE-(smooting)-C | [[455]](#_bookmark509) |
| Improper (Careless) Exiting the Road | (VS)-(DN)-LD-MOT-TE-(smooting)-C | [[455]](#_bookmark509) |
| Zigzag Driving | (VS)-(LD)-MOT-TE-(smooting)-C | [[447]](#_bookmark501) |
| \*Distance Violation to Front Vehicle | (VS)-(DN)-MOT-(smoothing)-C | - |
| \*Distance Violation to Side Vehicle | (VS)-(DN)-MOT-(smoothing)-C | - |
| Violation of The Lines | (VS)-(DN)-LD-MOT-(smoothing)-TE | [[454]](#_bookmark508) |
| Pedestrian on The Road | (VS)-(DN)-OD | - |
| Bike/Motorcycle on The Road | (VS)-(DN)-OD | - |
| Trailer [Oversized Car] on The Road | (VS)-(DN)-OD | - |

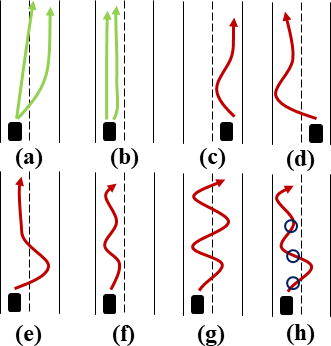


Figure 14: (a)-(d) are the trajectories with normal driving. (a) shows the normal lane changing, and (b) shows the normal straight driving. (c)-(e) are the three bases of zigzag driving. (c) is zigzag driving once without lane changing.

(d) is zigzag driving once with lane changing once. (g) is zigzag driving once with lane changing twice. (f)-(h) are some examples of more aggressive and frequent zigzag driving. The blue circles in (h) denote the sampling points by *HQ-sampling* with a big interval *t*0

Here, we provide alternative processing pipelines for zigzag driving as an exemplary application, along with a compar- ative analysis on the accuracy and complexity of each method. Zigzag driving on highways is a single-vehicle-involved event defined as frequent shifts to left and right in a short period of time *ts*. Figs. [14(c)-(e)](#_bookmark35) show the three bases of zigzag driving during the short period *ts*, in comparison with the normal driving (including the normal lane change shown in Fig. [14(a),](#_bookmark35) and the normal straight driving shown in Fig [14(b)).](#_bookmark35) These zigzag driving incidents include i) zigzag driving only once without lane change (Fig. [14(c)).](#_bookmark35) ii) zigzag driving once with lane change (Fig. [14(d)),](#_bookmark35) and

1. zigzag driving once with multiple lane changes (Fig. [14(e)).](#_bookmark35) The other cases of zigzag driving shown in Figs. [14(f)-(h)](#_bookmark35) can be decomposed into three base cases. To solve such an easy problem, one may take different approaches, including:
   1. *MOT-TP*: This solution uses Multi-Object Tracking (MOT) to extract cars’ motion trajectories. The overall process is as follows: Several sub-sequences of each trajectory are generated by using a sliding window with size *ts* (in order to save processing time, the stride can be set greater than 1). Then a sub-window with size *L* is used to extract possible peaks and trough points to be processed by Non-Maximum Suppression (NMS) to obtain the turning points. When the number of the turning points is greater than the threshold *nz*, this sequence will be determined as zigzag driving. Theoretically, *MOT-TP* is able to detect all cases of zigzag driving, regardless of the road pattern and without the need for detecting road lanes. The potential drawback of this method is that normal driving on sharp road curves may be considered zigzag driving.
   2. *LD-Markings*: First, the lanes are detected by instance segmentation. Then, similar to the MOT-TP method, the motion trajectories are extracted by MOT. The zigzag driving is determined by comparing the trajectory sub-sequences with the lane markings. The trajectory is determined as zigzag driving when the number of lane changes is greater than a threshold *nz* within a given time interval. The accuracy of this method varies based on the performance of the utilized algorithms for trajectory extraction and lane detection. It is not suitable for dirt and unlaned roads. It also misses zigzag driving with no lane changes, such as the examples in Figs. [14(f,h).](#_bookmark35)
   3. *Trj-Cls*: The Trajectory classification method skips modeling the road and the surrounding environment; instead, it directly applies supervised or unsupervised classification to the extracted trajectories to identify zigzag driving events. Similar to the *LD-markings*, the accuracy of this method depends on the accuracy of MOT used for trajectory extraction. It is flexible and can utilize different classification methods. However, this data-driven method requires a relatively large manually annotated dataset to maintain reasonably high classification accuracy.
   4. *HQ-sampling*: This method can be viewed as a simplified version of *LD-Markings*. It uses high-resolution data to accurately identify the plate license numbers (by Optical Character Recognition (OCR)). This solution can track each vehicle by employing plate license numbers to replace the tracking algorithms. Instead of using video, this high-quality data often is in the form of images, to be captured continuously at intervals *t*0, which may lead to inaccurate trajectory extraction. Similar to the *LD-markings* method, *HQ-sampling* determines zigzag driving by comparing the detected number of lane changes with the threshold *nz*. Its accuracy depends on the performance of the OCR, the lane detection algorithm, and the utilized sampling interval *t*0. The main shortcoming of this method is high complexity for short intervals, compromised accuracy for long intervals. This method may also undercount the lane changes if the sampling interval is selected large (e.g., it only counts zero lane changes in Fig [14(h)](#_bookmark35) with the three sample points).

Table 16: Comparison of the solutions to detect zigzag driving.

SW denotes sliding window used to search the peak and trough points.

|  |  |  |  |
| --- | --- | --- | --- |
| **Method** | **Complexity of Inference** | **Sources of Complexity** | **Accuracy** |
| *MOT-TP* | M | MOT+SW | H |
| *LD-markings* | L | LD+MOT | M |
| *Trj-Cls* | H | MOT+ML | H |
| *HQ-sampling* | M/H | LD+OCR | L/M |

Table [16](#_bookmark36) compares these four solutions in terms of accuracy and computation complexity. Note that the comparison is based on the assumption that the MOT algorithm performs well and a powerful trajectory smoothing method is deployed. Additionally, roadside video cameras are often fixed, meaning that lane detection is performed only once per scene and does not substantially affect the computation load.

As seen, there exist many alternative solutions for such a simple problem. Therefore, a thorough understanding of methods can help the researchers design the most effective processing pipeline for the problem at hand. It is worth mentioning that other trajectory-based tasks often have similar processing steps of (VS)-(DN)-LD-MOT-TE- (smoothing)-C, as shown in Table [15.](#_bookmark34) It means that some parts of processing pipelines can be shared among different problems, or transferable inference models can be used for multiple tasks to lower the cost.

# New Trends in Deep Learning

In this section, we review new trends in deep learning that are expected to substantially influence the field of video- based traffic safety analysis.

## Computer Vision by Transformers

We reviewed various DL methods for vision-based traffic video analysis in Section [5.](#_bookmark13) Most DL networks include Fully Connected (FC) layers, Convolutional Neural Networks (CNN), or Recurrent Neural Networks (RNNs) as their backbone. This journey witnessed several milestones such as the emerge of LeNet [[456]](#_bookmark510) in 1989, AlexNet [[110]](#_bookmark164) in 2012, VGG-Net [[111]](#_bookmark165) in 2014, and [GoogleNet[112]](#_bookmark166) in 2015. ResNet [[113]](#_bookmark167) was amongst the most surprising developments that beat Human perception with a 3.57% top-5 error rate in the ImageNet competition. Parallel to CV, DL methods are developed for sequential learning, mainly in the field of Natural Language Processing (NLP). For years, sequential learning was dominated by Gated Recurrent Units (GRUs) [[457]](#_bookmark511) and Long Short-term Memory network (LSTM) [[458],](#_bookmark512) until recently when a revolutionary framework known as Transformer is introduced by Google researchers [[459].](#_bookmark513) It has an encoder-decoder architecture and uses multi-head self-attention modules to capture longer internal dependencies in addition to the input-output dependencies in sequential data. Position embedding enables parallelizing the training process and capturing dependencies beyond the sequential relations. Technical details and different variants of transformers are discussed in [[459,](#_bookmark513) [460].](#_bookmark514)

Transformers are proven to be successful in capturing short-term and long-term dependencies in both NLP and CV tasks. The most classic work that uses Transformer architecture is [[461]](#_bookmark515) from Google, which outperforms the com- petitors in 11 NLP tasks. The emerge of Transformers is considered the end of the LSTM era in NLP, and can even challenge the position of CNN in CV tasks in the next few years. For instance, Google’s implementation of Trans- formers [[462]](#_bookmark516) achieved an unprecedented accuracy of 88.55% on ImageNet, taking advantage of transfer learning. They pre-trained the network on a very large dataset (e.g., JFT-300M), then fine-tuned if for ImageNet. Similarly, the authors of [[463]](#_bookmark517) achieved an 83.3% top-1 accuracy and beat the ResNet50 with a similar number of parameters.

They showed the Transformers’ capability on downstream tasks, such as detection and semantic segmentation. We expect to see more Transformer-based safety analysis frameworks in years to come, not only in CV tasks, but also for processing sequential data, such as trajectory extraction, tracing, and individual and collective behavior modeling of pedestrians, self-driving cars, and AVs.

## Federated Learning

One of the challenges in traffic safety analysis is processing massive volumes of RSU videos. Several approaches, such as cloud computing, edge/fog computing, down-sampling, resolution reduction, importance sampling, and event- triggered on-demand processing methods, are developed by researchers to tackle this problem while not missing key safety events. One key research direction is developing optimal strategies for data and model sharing so that more meaningful information is extracted by collective processing of the aggregated data in RSUs. One of these methods is using Federated Learning (FL).

Federated learning was first introduced by Google [[464]](#_bookmark518) in 2017 as a decentralized collaborative technique. Federated learning aims to address several practical issues in practical scenarios, such as vehicular edge computing. Some of these issues include: i) the data is often in silos for privacy problems; ii) the communication capacity is limited; iii) data is unbalanced in different local nodes, and iv) data not be independent and identically distributed (non-i.i.d), for example, in-board cameras in two vehicles from different regions can both record specific types of roads, but the roads in different regions often have different styles. Federated learning is categorized into three classes based on data partitioning [[465]:](#_bookmark519) i) horizontal federated learning, which has more overlapped features with fewer overlapped users;

ii) vertical federated learning, which has less overlapped features but with more overlapped users; and iii) federated transfer learning, with non-overlapping features and users. To train an FL model, the local nodes only train on their local data and upload the encrypted learned weights or gradients to the central server without sharing data. Then the central server aggregates this information to update the global model and release the model to the nodes for the next round of learning. Two baselines algorithms, known as FedSGD and FedAvg, are implemented in [[464].](#_bookmark518) Specifically, in each round of FedSGD, each local client updates once, and then the global model is updated based on the weighted average of the updated gradient from the clients. A little different from FedSGD, FedAvg performs more aggressively, in which the local client takes more steps for each central server update. The experimental result shows that FedAvg imposes less communication load compared to FedSGD to achieve the same accuracy. The authors of [[466]](#_bookmark520) proved the convergence of FedAvg under strong convexity and smoothness assumptions. In past years, some works have already used FL in smart transportation, such as a privacy-preserving traffic prediction introduced in [[467,](#_bookmark521) [468],](#_bookmark522) and FL-based Vehicle-to-Vehicle (V2V) and Vehicle-To-Everything (V2X) low-latency communication introduced in [[469,](#_bookmark523) [470].](#_bookmark524) We refer the interested reader to [[471]](#_bookmark525) for a more interesting and broader range of applications of FL.

It is noteworthy that FL still has some unresolved issues. Firstly, its reliability and robustness under uncertain condi- tions are not yet well established. Specifically, as discussed before, the center server has no access to the entirety of the local data and is unaware of local update progress. It means the aggregated model is much vulnerable to defending the introduced backdoor functionality if one or some nodes are malicious [[472].](#_bookmark526) Additionally, most practical FL networks consist of heterogeneous local nodes with varying learning ability and communication rates, which can challenge the overall robustness and performance of the system. After solving its issues, FL would be a promising solution for traffic safety analysis, as it provides a powerful tool to extract and analyze massive data volumes while protecting the privacy of road users. RSUs and in-vehicle processors can act as central and local processors of a large-scale FL system.

## Adversarial Learning For Safety Analysis

Despite the demonstrated power of DL methods in learning from massive data, the community is increasingly con- cerned about the security and reliability of neural networks. One reason for this concern is that small perturbations can easily fool a big DL network [[473],](#_bookmark527) which can lead to misleading results in traffic safety analysis and operation, espe- cially for self-driving cars. Fig. [15](#_bookmark40) demonstrates an example that the adversarial sample generated by Fast Gradient Signed Method (FGSM) [[474],](#_bookmark528) which easily fools MobileNetV2 to detect a traffic light as a fence.

Adversarial machine learning aims to alleviate these issues by exploring the vulnerabilities of ML algorithms and defending against potential attacks. The attacks can be divided into two main categories: evasion/exploratory attacks and Poisoning/causative attacks [[473,](#_bookmark527) [475].](#_bookmark529) The former cannot tamper with the model but feed carefully designed adversarially perturbed examples to the network in the testing phase. These data (sometimes imperceptible) can significantly change the feature representations and result in fatal misclassifications. In the latter case, the attacker injects malicious data samples into the training dataset to misguide the model training. It is a legitimate concern if one anticipates that adversarial samples are inserted in the training dataset using software backdoors [[476].](#_bookmark530) Alternatively,

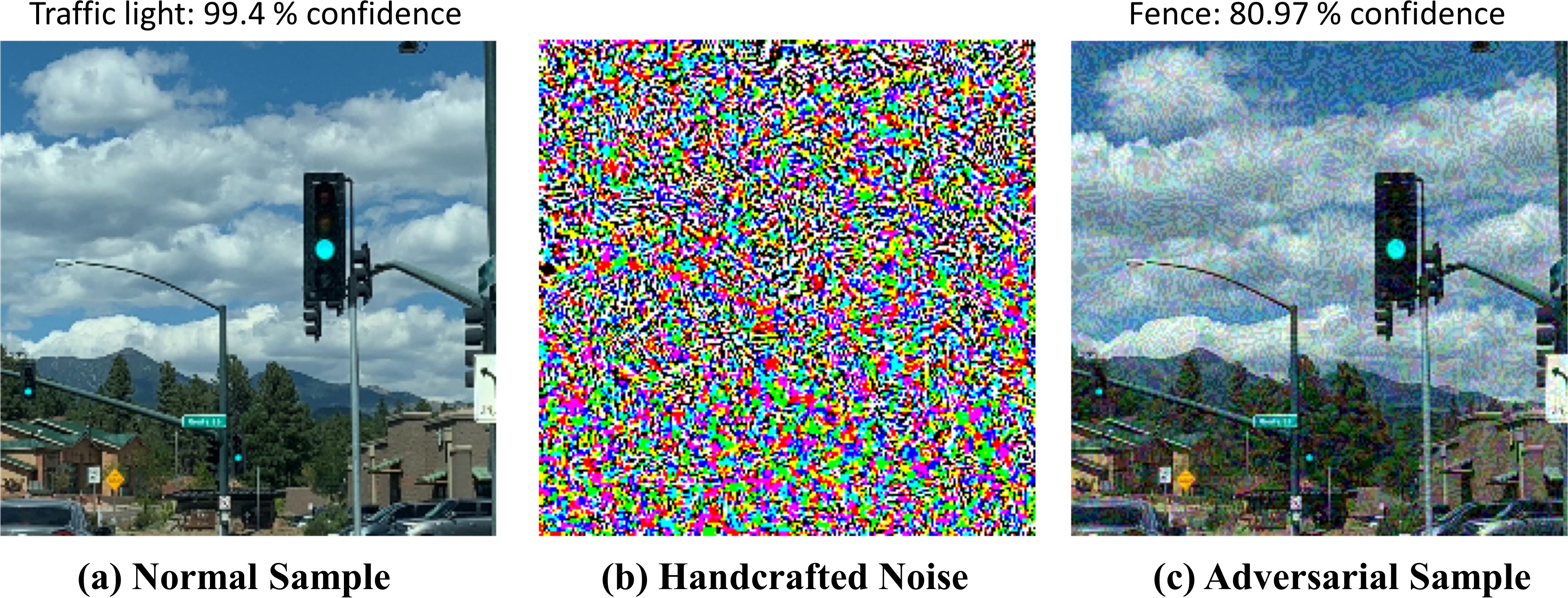


Figure 15: An example of adversarial samples generated by Fast Gradient Signed Method (FGSM) [[474].](#_bookmark528) The detector is MobileNetV2 trained on ImageNet. (a) is the normal sample, classified as "traffic light" by MobileNetV2, (b) is the hand crafted noise (adversarial attack), and (c) is the adversarial sample generated by adding hand crafted noise to the normal sample, classified as "fence" by MobileNetV2.

one way poison the training process is by explicitly attempting to corrupt the trained model. For instance, poisoning data samples can be added to cause gradient vanishing [[477].](#_bookmark531)

Indeed, one would suppose that the attacker and defender play a two-player game, where the defender expects to design a robust model against the adversarial samples. It augments the data by adding the adversarial samples in the training phase, and then solves a min-max problem. Another strategy is to try to recognize and filter out the adversarial examples [[478].](#_bookmark532) Since many attacks are implemented by tracking the gradient, some defenders (such as [[479])](#_bookmark533) attend to hide or change the gradient information. Some other defenders design robust optimization based on regularization methods against attacks [[480].](#_bookmark534)

Finally, we remind that these attacks or defense methods are often designed for specific or known situations. However, real-world applications are often exposed to unknown attacks. This concern can be even more critical when developing traffic-related frameworks. The driving safety analysis requires further investments in developing robust models using inverse learning. The models should undergo heavy inspections before being utilized in traffic control systems.

## Meta-Learning

Meta-Learning, aka learn-to-learn, aims to learn the learning process from other machine learning or deep learning tasks, and then apply this learned experience to guide the design and training process for a new task. It can generally learn the new task faster than the manual training; therefore facilitates designing a novel algorithm or framework merely by data-driven methods [[481].](#_bookmark535) To be more specific, in general learning, the optimizer only learns on the current dataset, and the objective function is defined only for the current task. However, meta-learning focuses on the elements of the learning phase (such as parameter initialization, optimizer, architecture, etc.) and learns how to generalize these elements across tasks and how to perform better on new tasks. Formally, the problem is presented by

[[482]](#_bookmark536) as:

min Lmeta *θ*∗(*i*)(*ω*)*, ω,* D(*i*) *,* (1)

*ω*

s.t. *θ*∗(*i*)(*ω*) = arg minLtask *θ, ω,* D(*i*) *,*

*θ*

where *ω* denotes the meta prior to be learned, *θ*∗(*i*)(*ω*) denotes the learned parameters on the dataset (*i*) for task *i* under the meta prior *ω*. meta and task denote the loss of meta-learning and the task itself, respectively. Meta-learning can be trained using a non-parametric setup by measuring the distance between the target and trained samples, and

L L

D

predicting the sample label based on the closest trained samples. A differentiable meta can be solved by gradient descent.

L

It is noteworthy that this concept is somewhat related to transfer learning but is also slightly different from it. Specif- ically, transfer learning aims to learn the regular and trainable parameters, such as the weights of the networks from other datasets or tasks, then fine-tunes the pre-trained model for a new task, while meta-learning tries to learn the

hyper-parameters from other tasks and then utilizes them to learn a new task from scratch. Both transfer learning and meta learning can help develop more accurate driving safety analysis, taking advantage of similar datasets.

## Unsupervised Spatiotemporal Representation Learning

Video data plays an essential role in traffic-related tasks; however, supervised learning can be prohibitively expensive in some traffic scenarios, such as driving anomaly detection, due to the high cost of data annotation. Under such limitations, unsupervised and self-supervised learning methods would be an appealing way of processing traffic video.

One approach to developing unsupervised learning is taking advantage of representation learning to translate raw input into more workable representations. An exemplary scenario would be representing video frames in a latent space that shows a substantial distinction between safe and unsafe traffic volumes.

Generally, the goal of unsupervised learning is learning data in a latent and often a lower-dimensional space, which of- fers temporal invariance and simplifies the downstream analysis. In 2021, He et al. [[483]](#_bookmark537) investigated the performance of four popular image-based unsupervised frameworks (Momentum Contrast (MoCo) [[484],](#_bookmark538) a Simple framework for Contrastive Learning of visual Representations (SimCLR) [[485],](#_bookmark539) Bootstrap Your Own Latent (BYOL) [[486],](#_bookmark540) and Swapping Assignments between multiple Views of the Same image (SwAV) [[487])](#_bookmark541) for the spatiotemporal representa- tion learning. The authors named the spatiotemporal invariant as *temporally-persistent*. Specifically, they anticipated that the high-level representation of the same video would be similar in different clips. These four frameworks take advantage of contrastive learning, which aims to maximize the similarity of positive samples and minimize the sim- ilarity of negative samples. Generally, the negative samples are the sampled clips from other videos. In MoCo, the authors introduced a creative method known as momentum coding, which constructs a dynamic dictionary to manage the representation of samples. This allows to quickly build and update the large and consistent dictionary to store much representation with a lower memory cost, which hugely enhances the ability of contrastive learning. BYOL and SwAV are considered versions of SimCLR and MoCo without using negative samples, respectively. They showed that these extended image-based frameworks could learn the spatiotemporal representation of video. A more interesting result is the competitive performance of these frameworks when combined with downstream tasks, compared to supervised learning in many tasks. These results provide a limitless possibility to deploy the unsupervised frameworks to industry and real applications.

# Traffic Datasets

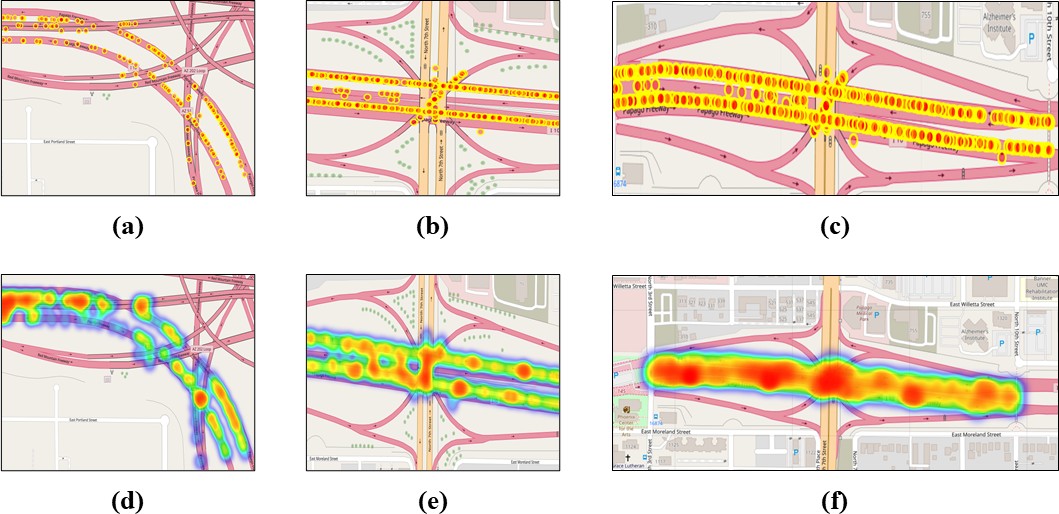


Figure 16: The visualization of some exemplary crash data. Each point in (a)-(c) denotes a crash, and (d)-(f) are the corresponding heatmaps.

Table [17](#_bookmark45) and Table [18](#_bookmark46) provide a relatively complete list of datasets that can be used for different aspects of video- based analysis for different CV-based traffic tasks. Data for trajectory analysis is often extracted from still cameras or drone-captured videos and used to understand microscopic-level (such as car-following models) to macroscopic-level traffic flow (such as traffic wave models) [[515].](#_bookmark569) Safety analysis of human-driven vehicles closely relates to video understanding tasks such as scene recognition, object detection, instance and semantic segmentation, developed for auto-driving vehicles. Traffic sign detection is another difficult problem due to using different variants for the same signs, uncontrolled and varying light conditions, the impact of weather conditions (rain, snow, fog, etc.), and the unpredictable traffic environment, especially when real-time processing is needed.

Table 17: Some popular traffic-related datasets.

**Category Dataset Size Features**

around 162, 000 frames

MIT traffic [dataset(2011)[123]](#_bookmark177)

from a 90 minutes long video sequence (30 fps)

Both pedestrian and vehicle movements;

with occlusions and varying illumination conditions

Trajectory MIT trajectory [dataset(2008)[488]](#_bookmark542) 577 radar tracks, 45 453 video tracks Multiple single camera view

analysis

a real highway (8 activities)

CVRR trajectory analysis datasets (2011) [[124]](#_bookmark178) 4 scenes: a simulated intersection (19 activities),

Units are pixels;

only contain spatial information

i-Lids–advanced vehicle detection [challenge[489]](#_bookmark543) 35000 images. 7 sequences with 25 fps. Consider daytime;

various locations in the UK

Three sub-datasets;

[NGSIM(2007)[490]](#_bookmark544) 45 mins+45 mins+ 30 mins

US-101 and I-80 for freeway scenario;

Lankershim Boulevard Dataset for arterial corridors scenario; each dataset is segmented with different congestion conditions

QMUL junction dataset(2012) [[125]](#_bookmark179) 1 hour video Busy traffic at a junction CamVid(2009) [[491]](#_bookmark545) 700 images, 32 classes, 10 min HD video with 30fps Support pixel-wise segmentation tasks;

provide 3D camera pose

Auto-driving tasks

Cityscapes [(2016)[492]](#_bookmark546)

Mapillary Vistas [Dataset(2017)[493]](#_bookmark547)

SYNTHIA(2016) [[494]](#_bookmark548)

5000 pixel-level annotated images

and 20000 coarse annotated images (weak-label)

25 000 high-resolution images; 66 classes for objection

37 instance-specific labels 13,400 frames of the city (real);

four video sequences of 50,000 frames (simulated); 13 classes

complex urban street scenes; record from 50 cities;

Various conditions regarding weather, season and daytime

Scene diversity; multiple seasons;

lighting conditions and weather

Up to 15 cars and 30 pedestrians per image;

KITTI Vision Benchmark Suite [(2012)[164]](#_bookmark218) 7481 training images and 7518 test images;

tasks of interest are stereo, optical flow,

visual odometry, 3D object detection, and 3D tracking

Diversity of annotations;

Berkeley Deep Drive [(2018)[495]](#_bookmark549) over 100K videos

diversity of geography, environment, and weather Unstructured environments;

Traffic sign detection

IDD (2019) [[335]](#_bookmark389) 10,004 images; 34 classes; 182 drive sequences

11 179 frames (8min 49sec, @25FPS);

TLR [(2009)[496]](#_bookmark550)

1. 168 instances of traffic lights

6600 frames with 7800 annotated objects; 49 classes of signs

LISA [(2012)[497]](#_bookmark551)

900 images

four-level label hierarchy; possibility for new tasks:

domain adaptation,

few-shot learning and behavior prediction

Hand-labeled;

tasks for traffic light detection and traffic sign detection

Recorded in the US;

Images from various camera types

Signs are divided into prohibitory, danger, mandatory,

[GTSDB(2013)[498]](#_bookmark552)

[BelgianTS(2014)[499]](#_bookmark553)

divided into 600 training images (846 traffic signs) and 300 evaluation images (360 traffic signs)

13,444 traffic sign annotations in 9,006 still images corresponding to 4,565

physically distinct traffic signs.

and other signs

Available for 2D and 3D testing

Plate detection

TT100K [(2016)[215]](#_bookmark269) 100000 images containing 30000 traffic-sign instances; 13427 images (5093training+8334test 15fps);

24000 annotated traffic lights

128 sign classes

BSTL [(2017)[500]](#_bookmark554)

ReId [(2017)[501]](#_bookmark555) 9.5hours from 8 locations

1. hours video;

Diversity of annotation

Cover a decent variety of road scenes and typical difficulties

Varied daytime;

multi-plates on a frame;

cameras placed on bridges above highways; relatively small objects

UCSD car dataset(2007) [[502]](#_bookmark556)

UFPR-ALPR [Dataset(2018)[503]](#_bookmark557)

878 cars tracked from the moment; 291 still cars recorded in parking lot

4,500 fully annotated images from 150 vehicles; 30 fps

>30,000 license characters;

Label with make, model, license plate location, plate texts

Different license color;

both vehicle and camera are moving

2000 Brazilian license plates; 14,000 alphanumeric symbols

SSIG [Dataset(2016)[504]](#_bookmark558)

Static camera view; character are segmented

Naturalistic Driving Studies often record and process the driver’s behavior, cognition, and perception of the sur- rounding environment without influencing or distracting the driver. This kind of data is generally large-scale since it requires long-term observations with multiple observed objects. The plate detection task involves drawing a bound- ing box around every detectable plate. A sub-task of plate detection is Optical Character Recognition (OCR), which requires understanding and validating engraved license plate numbers. Another twist to this problem is the angle of view. While most images are taken by roadside cameras, drone-based imagery datasets provide top-view images that solve some problems but poses new image processing challenges like human detection and small object detection.

It is notable that general Computer Vision (CV) datasets, presented in Table [19,](#_bookmark47) can be used to approximately evaluate the performance of developed algorithms if the desired traffic-specific dataset is not readily available. Here, we also want to mention some popular CV datasets (shown in Table [19)](#_bookmark47) since the most recent state-of-the-art algorithms deploy them as their evaluation criteria.

Table 18: Some popular traffic-related datasets (continue).

**Category Dataset Size Features**

Naturalistic Study

The 100-Car Naturalistic Driving [Study(2006)[505]](#_bookmark559) 2,000,000 vehicle miles;

SHRP 2 NDS [dataset(2012)[506]](#_bookmark560) more than 2 PB of continuous naturalistic driving data

43,000 hours of data

89,783 moving object instances;

Contains extreme cases of driving behavior; Event-based database

Multi-view video outputs; collected during a 3-y period from

more than 3,500 participants, aged 16–98 Tasks for moving and non-moving objects;

UAV

MOR-UA[V(2020)[507]](#_bookmark561)

Stanford Drone [Dataset(2016)[508]](#_bookmark562)

The highD [dataset(2018)[509]](#_bookmark563)

10,948 various scenarios;

>100 top-view scenes;

20,000 targets

annotated trajectories and id

16.5hous of measurements for 110,000 vehicles from 6 locations.

varied conditions of the environment;

labeled by aixs-aligned bounding boxes

Real-world scenario-based; varied types of targets

Real-world scenario-based; focus on highways

contain naturalistic behavior of road users

The inD [dataset(2019)[510]](#_bookmark564) contains more than 11500 road users;

10 hours measurement

Successor of highD, focus on intersections

Video-based Traffic events (Crash)

UCF-Crimes(2018) [[511]](#_bookmark565) 1900 sequences, 128hours Includes realistic anomalies such as fighting, road crash; DAD(2016) [[373]](#_bookmark427) 1730 sequences, 2.4 hours Spatio-temporal annotation

Include multi-crash sequences

No spatial annotation

Video captured by dashcam

[CADP(2018)[372]](#_bookmark426) 1416 sequences, 5.2 hours

Captured by CCTV; Include varied environment

NVIDIA AI CITY [challenge[512]](#_bookmark566)

Track 1: 31 videos (about 9 hours in total)

Track 2: 56,277 images,

36,935 come from 333 object identities

Track 3: 215.03 minutes videos 300K bounding boxes

Track 4: 200 15mins videos 30fps

Track 1: vehicle counting Track 2: vehicle Re-id Track 3: vehicle tracking

Track 4: Abnormal detection Anomalies can be due to

car crashes or stalled vehicles

classes typically based on Make, Model, Year

Fine-grained Vehicle

Standford [Cars[78]](#_bookmark132) 16,185 images of 196 classes of cars The cars images are taken from many angles;

Classification

Pedestrian Detection

[COMPCARS[79]](#_bookmark133)

Caltech [[163]](#_bookmark217) (2009)

CityPersons [[513]](#_bookmark567) (2016)

KAIST [[165]](#_bookmark219) (2015)

CVC-14 [[172]](#_bookmark226) (2016)

Web-nature: 136,726 (entire car)+27,618 (car parts), 163 car makes with 1,716 car models;

Surveillance-nature: 5000 car images

61k images with 192k pedestrians to train; 56k images with 155k pedestrians to test; 1273 unique pedestrians

5k images with 35k pedestrians; 19654 unique pedestrians

95,328 annotated image pairs (thermal and visible), 103,128 pedestrian annotation,

1182 unique pedestrians

5051 grayscale visible and thermal frame pairs; 9,319 pedestrian annotation (visible);

8,750 pedestrian annotation (thermal);

Web-nature data are labeled with bounding boxes and viewpoints;

the surveillance-nature images are in the front view

Objects with different occlusion; Objects with multi-scale; Sequential images

Built upon Cityscapes;

Record in different city with different weather; Objects with different occlusion;

Multi-spectral;

Include partial occlusion and heavy occlusion; Include day and night;

Sequential images

Multi-spectral; Include day and night; Sequential images;

Annotation include mandatory and unclear persons Multi-spectral;

FLIR [[514]](#_bookmark568) (∼2018) 9,711 thermal and 9,233 RGB images ;

15 Classes;

Sequential images;

Many pairs are unaligned;

**Crash Data:** Police-reported Crash Data, generally collected and stored by local, regional, state, and/or national government agencies after traffic crashes, can provide official, objective information about crash incidents. Sanitized crash data (e.g., personal information removed) is generally publicly available at the state level either online (e.g., Michigan crash data can be obtained at [[516])](#_bookmark570) or by a public records request. National level crash data in the US is available from the National Highway Traffic Safety Administration (NHTSA) via the National Automotive Sampling System General Estimates System (N[ASS-GES)[517]](#_bookmark571) which provides a national sample of police-reported crashes and the Fatality Analysis Reporting System (F[ARS)[518]](#_bookmark572) which provides details on nationwide fatal crashes. Crash data sets provide a wealth of information related to crash circumstances (including sequence of crash events and crash type), environmental conditions at the time of the crash, roadway characteristics at the crash scene, vehicle/road user information, and crash involved person-level characteristics (e.g., injury severity, age, gender, impairment, etc. ),

among other information. The Model Minimum Uniform Crash Criteria [(MMUCC)[519]](#_bookmark573) provides a voluntary guide- line for agencies with respect to the minimum data elements that should be included in crash databases and includes a description of 115 recommended data elements related to the incident, vehicle, person, roadway, and other categories. Crash data can be used to revise traffic and/or roadway plans, develop safety countermeasures, and explore associa- tions between crashes and traffic safety violations or other non-crash safety metrics. It can also be used to incorporate prior knowledge when analyzing traffic safety events.

**Missing Datasets**: There is a critical need to develop new datasets for traffic analysis that cover the underexamined aspects. As mentioned later in section [10.1,](#_bookmark50) some studies consider driving safety from the behavioral science per-

spective. For instance, eye motion tracking can be used to gauge the driver’s attention and detect distraction episodes [[520,](#_bookmark574) [521,](#_bookmark575) [522,](#_bookmark576) [523,](#_bookmark577) [524].](#_bookmark578) Very few datasets exist to facilitate such research. Among these, we found two datasets (The 100-Car Naturalistic Driving [Study[505]](#_bookmark559) and SHRP 2 NDS [dataset[506])](#_bookmark560) that offered a relatively large number of samples for driver behavior analysis. However, we noted that in these datasets, the activities for one vehicle in a specific scene are non-repeating, meaning that these datasets cannot provide driver-specific information. The authors of this study are currently working to develop a small dataset for driver-specific anomaly detection by collecting aerial imagery from test drivers’ behavior on specific scenarios multiple times. This dataset would enable profiling drivers based on their reaction to traffic conditions and use it to find abnormal behaviors that can be indicators of driving issues and potential crash risks. Also, very few datasets record traffic events from different perspectives. Datasets that can offer roadside imagery, along with aerial imagery and car-mounted cameras for synchronous analysis of traffic views, can open new research directions, particularly for multi-modal video analysis.The visualization of some exemplary crash data from Arizona Department of Transportation (ADOT) is presented in [Fig.16.](#_bookmark44)

Table 19: Some popular CV datasets.

**Dataset Size Features**

A set of datasets.

[MS-COCO[525]](#_bookmark579) 91 objects types. 2.5 million labeled instances in 328k images.

PASCAL V[OC[188]](#_bookmark242) 20 classes. 11530 images.

21841 non-empty synsets, 14,197,122 images. 1,034,908 mages with bounding box annotations.

[ImageNet[526]](#_bookmark580)

labeled by per-instance segmentation; more instances per category

A set of datasets.

Provide standard evaluation procedures;

contain significant variability in terms of object size, orientation, pose, illumination, position and occlusion

Organized according to the WordNet hierarchy.

# Safety Metrics

An essential objective of driving safety analysis is extracting *operational safety metrics*, which are quantifiable mea- sures extracted from traffic videos (or other data sources) that determine the relative risk of an event that may lead to a crash. Some important safety metrics that are used to analyze car crashes include:

* 1. **Temporal-based indicators:** Time to Collision (TTC), Extended Time to Collision (Time Exposed Time-to- Collision (TET), Time Integrated T[ime-to-Collision(TIT)[527]),](#_bookmark581) Modified TTC (MTTC), Crash Index (CI), Time-to-Accident (TA), Time Headway (H), and Post-Encroachment Time (PET).
  2. **Distance-based indicators:** Potential Index for Collision with Urgent Deceleration (PICUD), Proportion of stopping Distance (PSD), Margin to Collision (MTC), Difference of Space Distance and Stopping Distance (DSS), Time Integrated DSS (TIDSS), and Unsafe Density (UD);
  3. **Deceleration-based indicators:** Deceleration Rate to Avoid a Crash (DRAC), Crash Potential Index(CPI), and Criticality Index Function (CIF).

Reviewing different safety metric is out of the scope of this paper and we refer the interested readers to recent papers on safety metrics [[528,](#_bookmark582) [529,](#_bookmark583) [530].](#_bookmark584) As part of the Institute of Automated Mobility (IAM) project, the authors of this paper are working toward extending safety metrics into network-level metrics and developing a taxonomy of metrics for safety metrics for AVs based on the level of access required of ADS data [[387].](#_bookmark441)

# Miscellaneous Points

This section discusses some general facts about the driving safety analysis and reviews closely related research direc- tions. We conclude by mentioning key areas and emerging topics that require further investigations.

## Study From Human Condition And Psychology Perspective:

It is notable that understanding and interpreting traffic patterns, especially for human-driven vehicles, involves be- havioral and psychological factors. Some studies study traffic safety from a deeper perspective of assessing driver’s cognition and mental capacity. For instance, [[531,](#_bookmark585) [532,](#_bookmark586) [533,](#_bookmark587) [534]](#_bookmark588) use inventories or questionnaires to investigate the correlation between driving quality and general personality measures. Driving inventories in this context include the Driving Behavior Inventory (DBI), the Drivers’ Skill Inventory (DSI), and Montag Driving Internality and Externality

Scales (MDIE). Some other studies including [[535,](#_bookmark589) [536,](#_bookmark590) [537,](#_bookmark591) [538,](#_bookmark592) [539]](#_bookmark593) analyze aggressive driving behaviours affected by the driver personality. The impaired driving performance caused by Synthetic Cannabinoids (SC) is investigated in [[540]](#_bookmark594) based on the collected blood samples. This study concludes that the SC is not the only key factor causing the reduced driving skills since the drivers often use other potent psychoactive drugs simultaneously. The impact of landscapes on drivers’ mental status is investigated in [[541,](#_bookmark595) [542,](#_bookmark596) [543,](#_bookmark597) [544].](#_bookmark598)

Some car manufactures have utilized AI systems to assess drivers’ cognition systems, for instance, by monitoring eye motion and alerting drivers when distracted [attention[37].](#_bookmark91) Other AI systems aim to gauge drivers’ emotions and drowsiness by cameras and microphones[[36].](#_bookmark90) This line of research mainly relies on sampling techniques and often can offer some empirical results, which is hard to examine and generalize. Therefore, these methods have a long way ahead for being widely adopted by the engineering community.

## Relation to AVs

AI platforms have been utilized in recent years to build AVs. AVs use different technologies such as regular cameras, radar, optical radar, and GPS, along with computer vision and learning methods, to realize autonomous driving. In 2015, Tesla started to commercialize ’Autopilot’ features in its cars, and soon afterward, other manufacturers joined the race. Currently, there are over 250 autonomous vehicle companies, including automakers, technology providers, services providers, and tech start-ups, that are taking serious steps to make self-driven or driver-less cars a reality. According to [[545],](#_bookmark599) the top five autonomous vehicle companies are Waymo, General Motors’ Cruise division, Tesla, Baidu, and Argo AI (Ford Motor).

The official level classification system for autonomous driving is defined by the Society of Automotive Engineers (SAE International) [[546]](#_bookmark600) and approved by the National Highway Traffic Safety Administration (NHTSA). The standard describes the five autonomy levels including [[547]:](#_bookmark601)

* + - Level 0 (no automation): The human driver has full authority to operate the car, and can be assisted by warning and protection systems during driving.
    - Level 1 (driving support/hands on): Provide driving support for one operation of the pay-off reel and accel- eration/deceleration through the driving environment, and the human driver operates other driving actions.
    - Level 2 (partial automation/hands off): The vehicle can fully control the car by acceleration, braking, and steering; however, the driver should keep monitoring the environment and be prepared to intervene immedi- ately at any time.
    - Level 3 (conditional automation/ eyes off): The unmanned driving system completes all driving operations. According to the system request, the human driver provides an appropriate response.
    - Level 4 (highly automated/ mind off): The unmanned driving system completes all driving operations. Ac- cording to system requests, human drivers do not necessarily need to respond to all system requests and limit road and environmental conditions.
    - Level 5 (fully automated): The unmanned driving system completes all driving operations. Human drivers take over when possible. Drive on all roads and environmental conditions.

One of the biggest questions surrounding AVs is: How safe is safe enough? This is a controversial issue. [Statistics[548]](#_bookmark602) show that AVs are very safe, and AV-caused crashes are rare. It is still hard to get an accurate self-driving car death toll since some AVs are still developing or testing. Tesla claims that their ADS processing time is four times safer than regular cars, while operating in Autopilot mode. Their estimation is one fatality per 320 million miles driven. However, people still have doubts about the safety performance of autonomous vehicles. As reported in [[549],](#_bookmark603) a self- driving Uber car (a test vehicle) hit and killed a woman in Arizona partly because it failed to recognize the pedestrian jaywalk, but further investigations found the pedestrian at fault, and Tempe Police called the crash unavoidable since the pedestrian had been crossing outside of a crosswalk [[550].](#_bookmark604) Also, there is a cultural barrier to the broad utilization of AVs, especially in developing countries. To solve these challenges, characterizing safety metrics and their thresholds for AVs is of great importance. These analyses, along with the low crash rate of AVs, can provide further relief to society for using AVs. Most AVs calculate safety metrics and use AI methods to react to safety issues appropriately. However, they see the events and the traffic from their own perspective. Developing network-level safety metrics can provide a holistic assessment of the overall traffic safety level when AVs join the regular traffic flows.

## Relation to Vehicle Insurance Evaluation

The primary use of auto insurance is to provide financial protection against physical damage or bodily injury re- sulting from traffic collisions and against liability that could also arise from incidents in a vehicle. In general, the

insurance company calculates the insurance premium based on different factors that affect the customer’s chance of being involved in a crash. The factors include age, car type, driving history, where the customers live, and other fac- tors. Therefore, developing safety models that integrate these factors and predict crash rates can be used by insurance companies for more accurate estimations [[551].](#_bookmark605)

Recently, a fully autonomous vehicle insurance pricing [[552]](#_bookmark606) system was built based on such information. Moreover, a system [[553]](#_bookmark607) that uses vehicle operation data collected via mobile devices for vehicle insurance pricing. Studies on traffic safety metrics could provide more precise and targeted information to these systems to determine a more flexible and reasonable insurance policy for both customers and companies.

## Crowd-sourcing for Traffic Analysis and Driving Safety

Noting the wide use of smartphones with accurate positioning systems, crowd-sourcing can be used to collect vehicle motion trajectories, crash incidents, etc., for network-level safety analysis. For instance, [[554]](#_bookmark608) uses crowd-sourcing to provide an early warning to drivers regarding road safety hazards due to construction work, defective street cuts, bumps, etc., using a cellphone-based App and embedded accelerometer readings. Indeed, part of the navigation software features in GoogleMAP and Waze is based on cro[wd-sourcing[555].](#_bookmark609) However, most crowd-sourcing methods share raw data; therefore, using more elegant DL-enabled safety analysis algorithms can substantially enhance the efficacy of the produces advisory messages.

## Vehicular Edge Computing

When the computation load is beyond the local servers’ power, cloud computing is used. However, cloud computing may cause intolerable computation delays and interruptions due to networking delays. For these scenarios, edge emerging is adopted by running computations on servers located at the network edge, to mitigated networking and scheduling delays [[556].](#_bookmark610) For instance, the idea of offloading heavy computations tasks by AVs to RSUs is proposed in [[557].](#_bookmark611) These distributed nodes can share their computation ability that decentralizes the stress of the large network and reduces bandwidth consumption and response time among various servers and end-users. Users are allowed to access the physically closest servers to operate their real-time applications with good Quality of Service (QoS) and low latenc[y[558].](#_bookmark612)

Recently, the idea of deploying Vehicular Edge Computing (VEC) in Vehicular Ad Hoc Networks (VANETs) is pro- posed (Fig. [17).](#_bookmark51) Conventionally, VEC consists of three layers [[559]:](#_bookmark613) User Layer, Edge layers, and Cloud Layer. The User Layer is composed of Vehicular Terminals (VTs), mainly as smart vehicles. Terminals perform sensing the environment, Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communications, limited computation tasks, and part of the storage. Edge Layer mainly consisted of Road-Side Units (RSUs), handle caching, computation, offloading, and deliver low-latency diverse service. RSUs are widely distributed on the roads and have more power- ful computation capacity and larger storage space. RSUs deploy wireless communication protocols (such as WLAN, 3GPP, 4G, 5G, etc.) to guarantee reliable links that connect the Cloud and User Layers. It should be noted that the majority of data computation and storage is carried out in this layer. Cloud Layer, which consisted of cloud servers, has the greatest computation capacity and the higher storage capacity. This layer is desired to support centralized control, data aggregation, and global management and optimization. These tasks often are complicated and time-consuming; however, latency-sensitive tasks should not be included. To achieve enhanced performance, VECs use several tech- niques, including Content caching, redundancy (the content the terminal potentially requests), and history content on the edge servers in the proximity of users. This reduces the traffic flow across the whole network and enhances the user e[xperience[560,](#_bookmark614) [561,](#_bookmark615) [562].](#_bookmark616) In order to solve computation issues, task Offloading is used to transfer the excessive computations from local servers (potentially in vehicles computers) to the closest RSUs [[557,](#_bookmark611) [563,](#_bookmark617) [564].](#_bookmark618) Software- Defined Networking [(SDN)[565]](#_bookmark619) separates the control plane and data plane that allows easy switches reconfiguration for flexible network management.

VEC addresses a wide range of problems for traffic safety. It facilitates real-time collecting and processing data from smart vehicles and infrastructures to optimize navigation to avoid congestion and warn the surrounded vehicles to avoid collisions or other incidents. Also, each participating VEC receives the information and is allowed to adjust its strategy (such as Platoon [[566]).](#_bookmark620) Moreover, beyond safety-related scenarios [[567],](#_bookmark621) VEC also make high traffic demand applications possible, such as video [streaming[568,](#_bookmark622) [569],](#_bookmark623) Augmented Reality [(AR)[570],](#_bookmark624) and in-vehicle Infotainment Service (such as online g[aming)[571].](#_bookmark625) The current challenges and active research problems in VEC include transmis- sion reliability, service capacity, integration, scalability, security and user privacy, and economic considerations.

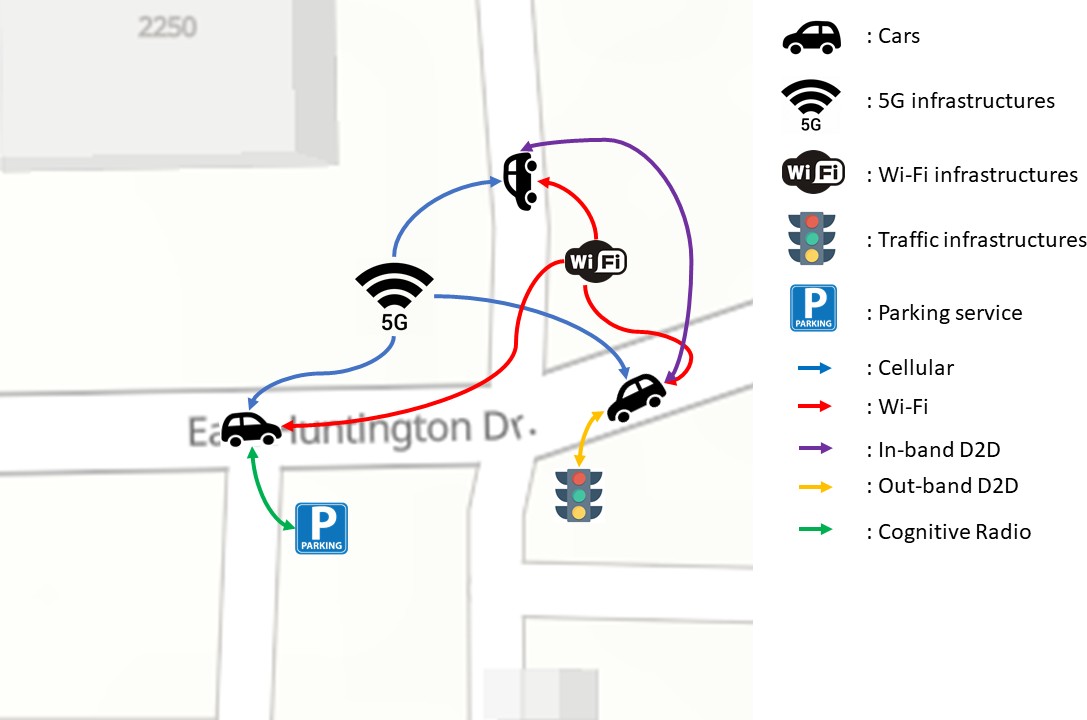


Figure 17: VANETs framework.

# A Roadmap of Traffic Safety Development in Vehicle Industry

Since 2010, conventional safety technologies such as *Automatic Emergency Braking* (AEB) and *Electronic Stability Program* (ESP) have become prevalent for most private and commercial cars [[572].](#_bookmark626) Starting in 2016, more vehicle manufacturers such as Toyota, Honda, GM, and BMW have equipped advanced driver-assistance systems, like *Lane Keeping Assist* (LKA) and *Adaptive Cruise Control* (ACC), for more standard models to improve the safety of vehi- cles [[573].](#_bookmark627) These subsystems can achieve basic steering, acceleration/deceleration, and lane changing under specific circumstances. According to [[574],](#_bookmark628) these advanced driver assistance technologies have reduced the accident rate by about 25 % on average. More importantly, the single-vehicle and head-on collisions have already been reduced by about 50 % [[575],](#_bookmark629) meaning that the future focus of safety features would be on the turning and crossing scenarios. In such scenarios, more advanced driver assistance systems are required to handle the active safety of drivers and passengers with complex external interactions.

In 2019, Tesla announced its *Full Self-Driving* (FSD) service on private transportation [[7].](#_bookmark61) This is the first case of SAE level 3 automation on the mass production level. Soon afterward, Google and NVIDIA presented their level 4

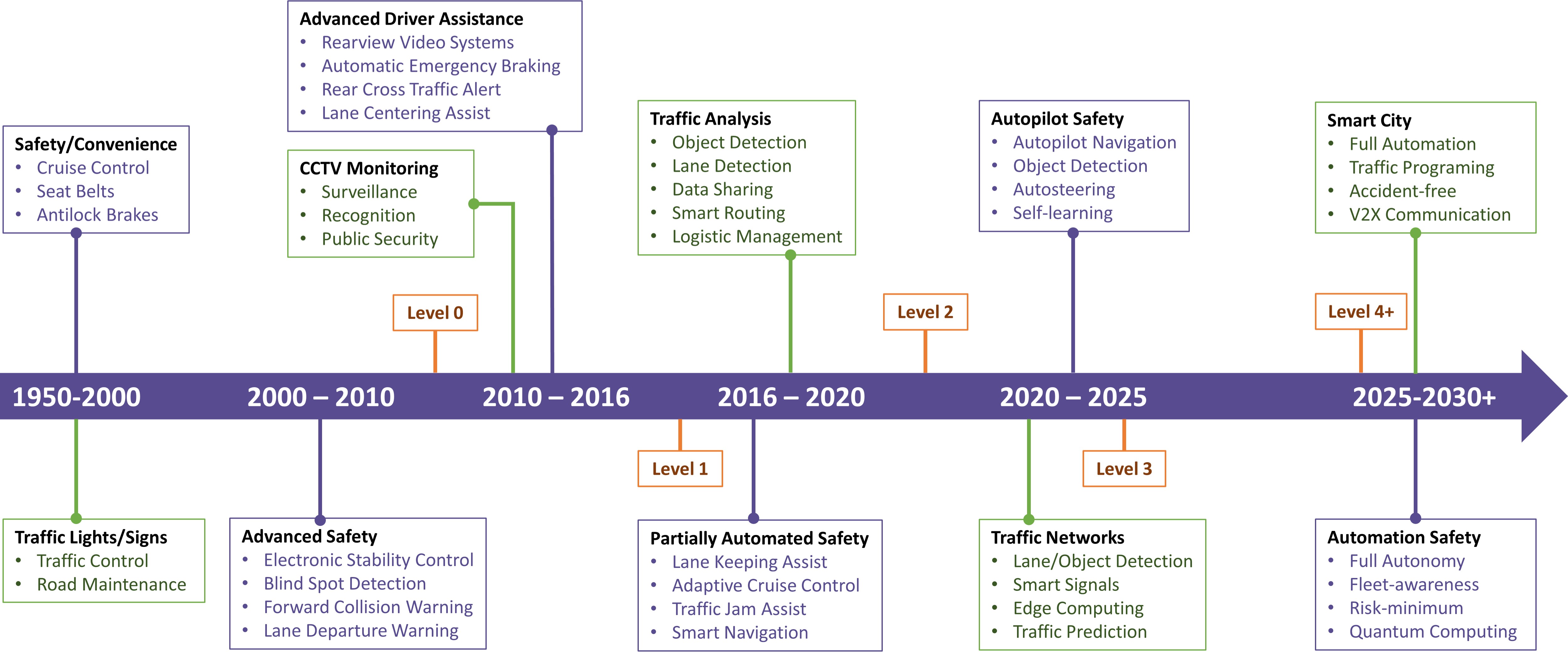


Figure 18: A roadmap for traffic safety development with vehicle automation level.

autonomous vehicles [[9,](#_bookmark63) [576,](#_bookmark630) [577],](#_bookmark631) while GM and Amazon announced their level 5 autonomous shuttles later in 2020 [[10,](#_bookmark64) [11](#_bookmark65)]. The above companies all presented their mature solutions for self-driving in both private and commercial transportation. Tesla and Waymo also introduced the self-driving semi-truck for commercial and industrial utilization [[14,](#_bookmark68) [15].](#_bookmark69)

Vehicle automation mostly benefited from the vast experience of vehicle production in the last decades, while smart traffic network management systems are still in their infancy. Part of this lag is due to the need for heavy investment in networking, the internet, and road infrastructures. The present traffic network systems utilize features such as Closed-Circuit Television (CCTV)-based traffic monitoring, incident detection, and traffic flow analysis based on GPS information and real-time data analysis [[16,](#_bookmark70) [17,](#_bookmark71) [19,](#_bookmark73) [21].](#_bookmark75) These safety features have not been widely utilized in suburban areas and require further investment and appreciation from the local departments of transportation [[578].](#_bookmark632)

We conclude this section by presenting key milestones and the future roadmap of the vehicle-based and network-level traffic safety features in Fig. [18.](#_bookmark53)

# Key Challenges and Open Problems

We reviewed the applications of DL in video-based traffic safety analysis along with the envisioned future directions in Section [7.](#_bookmark37) Although the use of DL methods for different aspects of driving safety analysis gains more momentum every year, there still exist numerous challenges and issues to be addressed.

## Data Domain Drift

Domain data drift is one of the most practical problems when applying deep learning methods in traffic analysis, especially in some custom tasks (i.e., tasks that have specific requirements and/or when proprietary data is utilized).

The proposed network often are trained and evaluated on public popular datasets (such as datasets in Table [17](#_bookmark45) and Table [18).](#_bookmark46) Such datasets are usually neat, distortion-free, and well-annotated. This is not the case for most locally col- lected datasets. Therefore, training DL networks from scratch or utilizing networks that are pre-trained on benchmark datasets for new tasks can yield disappointingly poor performances. This performance shift is frequently reported due to the proprietary datasets’ domain shift, such as different resolutions, noise levels, altered perspectives and field of view, etc. We experienced the same issue in our network-level metrics analysis project [[387].](#_bookmark441) In this work, we aimed to extract network-level metrics from surveillance videos. As part of this problem, we need to detect and trace vehicles; however, using pre-trained benchmark detection algorithms, such as FCOS and RetinaNet, yield poor performance. Finally, we ended up using the combination of YOLOv5 and DeepSort for tracking vehicles on the road, which gave accepted results. This is not specific to our work and often occurs when applying a DL framework to new problems, especially for practical systems. Further investigations of more elegantly designed transfer learning approaches or formal ways of fine-tuning pre-trained networks can be a game-changer. Another possibility is using meta-learning, which is briefly discussed in Section [7.4,](#_bookmark41) to learn how to learn efficiently and optimally. This may decrease the cost of annotation and allow the fast deployment of DL frameworks in this context.

## Data Processing Labor Cost

Labor cost is another limiting factor for developing learning-based traffic modeling frameworks, especially for data preparation and annotation. For instance, the 100-Car naturalistic driving study [(2006)[505],](#_bookmark559) one of the most popular traffic datasets, collected data from about 100 cars totally driving approximately 2,000,000 miles and 43,000 hours, and took about four years to complete. We agree that not every problem needs this huge of a dataset; however, the traffic- related work needs this kind of data to create reliable automated analysis frameworks. Usually, annotation requires a big team of experts to perform annotations and tackle the difference of opinion. This can impose unaffordable costs and time delays for budget-constrained projects. Alternative solutions are using semi-supervised learning to label data, unsupervised learning (such as unsupervised spatiotemporal representation learning discussed in Section [7.5)](#_bookmark42)), and data augmentation methods to mitigate the need for massive annotated datasets.

## Modeling Complexity

Developing data-driven and mathematical frameworks to model traffic flow and safety risks remains a challenging issue. Part of the reasons is the difficulty of modeling the environment, a huge number of factors with interlaced roles, the impact of human factors and cognition, and the relations between different vehicles, which creates a complex system to model. Several studies tried to model complicated traffic conditions. Some studies including [[579,](#_bookmark633) [580,](#_bookmark634) [581,](#_bookmark635) [582,](#_bookmark636) [583]](#_bookmark637) applied conventional methods to create surrogate safety models, while other works such as [[584,](#_bookmark638) [585,](#_bookmark639)

[586,](#_bookmark640) [587,](#_bookmark641) [588,](#_bookmark642) [589,](#_bookmark643) [590,](#_bookmark644) [580,](#_bookmark634) [591]](#_bookmark645) deployed statistical models to analyze traffic data. More recent works use DL for modeling purposes. For instance, DL frameworks are utilized by [[592,](#_bookmark646) [593,](#_bookmark647) [594,](#_bookmark648) [595,](#_bookmark649) [596]](#_bookmark650) for traffic prediction, by [[597]](#_bookmark651) for vehicle behaviour prediction, and by [[598,](#_bookmark652) [599,](#_bookmark653) [500]](#_bookmark554) for traffic classification. Although these works achieve excellent performance, they only modeled some specific scenarios (e.g., intersection, ramp merge, etc.). A general model that can briefly represent real road traffic conditions, perhaps by integrating the existing models, is still considered an open research problem.

## Algorithm Reliability and Efficiency:

Although DL methods have shown superior performance in simple image-based tasks such as object recognition, object tracking, and instance segmentation, they can be prohibitively unreliable when it comes to modeling multi- factor and multi-faceted phenomena that involve extracting complicated tasks by processing videos in real-time.

It is known that many DL-based algorithms deployed by traffic systems and AVs, such as [[129,](#_bookmark183) [108]](#_bookmark162) for object de- tection, [[600,](#_bookmark654) [601]](#_bookmark655) for stereo matching, [[602,](#_bookmark656) [603]](#_bookmark657) for optical flow. With recent advances in high-computational processing platforms, this issue seems to be mitigated day by day. More and more studies provide evidence for AVs’ safety and accuracy of DL-based traffic monitoring systems to alleviate cultural barriers in using DL-powered tech- nology and replacing humans with computers. However, still, some manufacturers like Tesla emphasize their products still require active driver [supervision[604].](#_bookmark658)

For conventional traffic analysis, the use of DL-based algorithms is not critical and does not directly compromise safety. However, the more widespread use of these algorithms can provide a better understanding of traffic safety in general. It can improve traffic risks by offering design hints to transportation infrastructures and real-time warnings to the cars on the road.

## Model Explainability

There exists a known performance-explainability trade-off in developing DL frameworks. One may explore the as- sociation among features from traffic scenarios (such as the association between crash rate and traffic volume) by statistic learning or simple models (such as linear regression or logistic regression). These methods are generally easy to explain and interpret. On the other hand, data-driven DL methods often show higher capabilities in extracting useful information for massive data; however, they are viewed as *black boxes* with limited *explainability*. This hinders extracting interpretable results, conceptual interpretations, and useful design guidelines from the developed models.

Currently, developing explainable AI platforms is considered an emerging field where efforts are made to make DL frameworks more explainable and easy to comprehend. For instance, visualizing and translating latent features into more meaningful representations in justification and dialogue system [[605]](#_bookmark659) is gaining higher momentum. Alterna- tively, one may intend to explain the local parts of the model. It can be addressed by using an interpretable model to imitate the behavior of an uninterpretable model. For example, there are some works that use local interpretable model-agnostic explanations (LIME) [[606]](#_bookmark660) to explain the selected data points in multiple applications, such as time series forecast [[607],](#_bookmark661) medical imaging [[608].](#_bookmark662) We expect that developing explainable and interpretable models would be a potential paradigm in traffic safety analysis and autonomous driving.

## Equipment Support:

Scarcity of data and the lack of sufficient monitoring infrastructure is another drawback. For instance, in the state of Arizona, more than 441 public cameras are used by the ADOT to monitor traf[fic[609],](#_bookmark663) but there are a total of 144,959 [miles[610].](#_bookmark664) This means that a lot of roads have not yet been fully covered by surveillance cameras.

## Privacy and Secrecy

Another barrier of common spread use of DL-algorithm for safety analysis is that traffic video contains personal information such as human face and plate numbers, which raises privacy concerns. We believe that publishing more traffic video repositories with removed Personal Identifiable Information (PII) can substantially accelerate the rate of discovery without compromising people’s safety.

## Model/Data Safety and Adversarial Learning

Trained DL networks can be susceptible to adversarial attacks that try to disrupt the model’s operation by injecting falsely annotated and misleading data points. This issue often refers to a topic known as adversarial learning (more detail, see Section [7.3).](#_bookmark39)

Imagine a few crafted adversarial examples that can totally mislead the model to make a wrong decision or introduce backdoors to the system [[611].](#_bookmark665) This issue is not easily imperceptible but significantly dangerous, especially for self- driving vehicles and RSU-based safety control systems. Developing high-standard defense strategies for traffic-related models is a top priority, and inverse learning can play an essential role in this respect.

## Naturalistic Driving Data:

Although some naturalistic driving data were collected for traffic flow and transportation research, such as Next Gener- ation Simulation (NGSIM) [data[490],](#_bookmark544) open-source naturalistic driving data for safety evaluation of vehicles are rarely reported. Since for vehicle safety analysis, some quantitative data of each vehicle are required, such as location, speed, acceleration, and heading angles, advanced technology need to be developed and applied to accurately obtain these measurements. When cameras are applied, computer vision and related to objective identification and tracking algo- rithms, based on ML or DL, need to be specifically developed, especially towards real-time processing. Some recent available naturalistic driving data obtained by drones, such as LevelX [[509,](#_bookmark563) [510],](#_bookmark564) can provide necessary pre-processed data for safety analysis purposes. However, these data are processed offline and expensive.

## Conflict of Responsibility

Compared to conventional driver assistance technologies, companies such as Tesla, NVIDIA, and Google prefer to use neural network-based models to handle most of the driving decisions in complex environments. As mentioned earlier, Tesla has announced the first Full Self-Driving (FSD) service on private transportation in 2019 [[7].](#_bookmark61) The system includes traffic-aware cruise control, autosteer, auto lane change, autopark, traffic sign control, and navigate on autopilot (Beta). Based on these features, the later Tesla products can be considered SAE level 3 vehicles. Almost the same time, Waymo has launched an SAE-4 taxi service in Phoenix, Arizona [[9],](#_bookmark63) as one of the first driver-less transportation services in the country. Also, Intel’s mobile eye [[612,](#_bookmark666) [613],](#_bookmark667) and Nvidia’s Drive [[614,](#_bookmark668) [615]](#_bookmark669) systems are other examples of SAE level 4 AVs. The GM Cruise Origin [[10],](#_bookmark64) and Amazon Zoox [[11],](#_bookmark65) presented almost fully-autonomous buses, toward developing SAE level 5 AVs. However, due to the conflict of responsibility between manufacturers and customers, some corporations abstain from declaring higher levels of autonomy. Some suppliers call their service SAE-2 [[616],](#_bookmark670) since the SAE-3 and higher levels of autonomy would require more strict regulations and would incur higher levels of responsibility to the manufacturer when a crash occurs [[546].](#_bookmark600) This might cause inconsistency and interoperability issues between the connected AVs and smart traffic systems in future developments.

## Fusion of AVs and the Future Traffic Network

Despite the rapid growth of both autonomous driving and smart traffic networks, very few works discuss the interop- erability and integration of such systems. A recent book [[617]](#_bookmark671) reviews the deployment of autonomous shuttles and self-driving technologies in various scenarios. [[618]](#_bookmark672) on the other hand, only discussed the applications of smart traffic techniques on AVs. A key question of "how to connect self-driving vehicles to the smart traffic network?" remains largely unanswered. The present smart traffic networks mostly rely on active environment sensing, then pass the infor- mation to fixed terminals (mobile device, APP) [[21].](#_bookmark75) These features are usually not utilized by current vehicle models, nor equipped by older models. A lawful document is expected to push these safety features to wider use.

Overall, developing efficient and sustainable AI-based traffic systems requires universal standards and guidelines through closer cooperation between different entities, including researchers, technology developers, law enforcement authorities, and operational teams. Besides, the communication between AVs from different manufacturers is limited. The dataset collected by corporations is labor costly, and privacy-sensitive [[619].](#_bookmark673) Apparently, large vendors are hesitant to share their datasets to keep their leverage in the competing AV market. This causes difficulty for researchers to obtain useful datasets and may lead to safety concerns [[620].](#_bookmark674) Implementing stronger intensives for data sharing, and standardizing the development process can further power this line of research.

# Conclusion

This paper reviewed DL methods that can be used for different aspects of video-based traffic safety analysis. We reviewed methods, tools, and datasets that are recently developed by the research community and industry. We high- lighted key achievements and mentioned areas that need further investigation. For example, we enumerate areas that require more advanced tools and also collecting well-annotated datasets. Some examples include but not limited to the need for developing DL algorithms, tools, and datasets for aerial traffic monitoring systems, more advanced video-based action recognition systems, integrative analysis of multi-modal traffic image and sensor data, extending individual safety metrics into network-level safety metrics, formal ways to develop safety metric distributions, finding

associations between network-level safety metrics and crash rate, developing online safety metric extraction tools, and developing end-to-end frameworks to translate safety risks into traffic advisory messages. We also made connections to closely related research areas, including AVs, Crowd-sourcing for traffic analysis, and driver’s behavioral patterns and psychological profiles, and the insurance industry. Our hope is that this paper will help computer scientists solve traffic safety problems, particularly areas that need further investigation. This paper also aimed to help traffic engineers and personnel to identify and use existing open-source tools for their problems.

# Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

# Acknowledgment

We would like to thank Drs. Junsuo Qu and Greg Leeming for his insightful comments. We are grateful to Arizona Commerce Authority, Intel Corporation, State Farm Insurance, Arizona Department of Transportation, and the Institute for Automated Mobility (IAM) for their continued support of this project.

# References

1. Global Status Report on Road Safety. World Health Organization; 2018. Available from: [https:](https://www.who.int/violence_injury_prevention/road_safety_status/2018/English-Summary-GSRRS2018.pdf)

[//www.who.int/violence\_injury\_prevention/road\_safety\_status/2018/English-Summary](https://www.who.int/violence_injury_prevention/road_safety_status/2018/English-Summary-GSRRS2018.pdf)

[-GSRRS2018.pdf](https://www.who.int/violence_injury_prevention/road_safety_status/2018/English-Summary-GSRRS2018.pdf).

1. ;. Available from: [https://www.statefarm.com/simple-insights/auto-and-vehicles/latest-car](https://www.statefarm.com/simple-insights/auto-and-vehicles/latest-car-safety-features-becoming-musthaves)

[-safety-features-becoming-musthaves](https://www.statefarm.com/simple-insights/auto-and-vehicles/latest-car-safety-features-becoming-musthaves).

1. Dinita M. Best road design software for PC [2020 Guide]; 2019. Available from: [https://windowsreport.](https://windowsreport.com/road-design-software/) [com/road-design-software/](https://windowsreport.com/road-design-software/).
2. ;. Available from: <https://www.bentley.com/en/solutions/road-design-and-analysis>.
3. KIRKLAND G. How new technologies have changed the automotive industry; 2019. Available from: [https:](https://www.oponeo.co.uk/blog/how-new-technologies-have-changed-the-automotive-industry)

[//www.oponeo.co.uk/blog/how-new-technologies-have-changed-the-automotive-industry](https://www.oponeo.co.uk/blog/how-new-technologies-have-changed-the-automotive-industry).

1. ; 2020. Available from: [https://www.oponeo.co.uk/blog/how-new-technologies-have-changed-](https://www.oponeo.co.uk/blog/how-new-technologies-have-changed-the-automotive-industry#%3A~%3Atext%3DThe20Growth20of20Autonomous20Technology%26text%3DMost20modern20cars20feature20autonomous%2Cand20work20out20potential20collisions) [the-automotive-industry#:~:text=The20Growth20of20Autonomous20Technology&text=Most20](https://www.oponeo.co.uk/blog/how-new-technologies-have-changed-the-automotive-industry#%3A~%3Atext%3DThe20Growth20of20Autonomous20Technology%26text%3DMost20modern20cars20feature20autonomous%2Cand20work20out20potential20collisions) [modern20cars20feature20autonomous,and20work20out20potential20collisions.](https://www.oponeo.co.uk/blog/how-new-technologies-have-changed-the-automotive-industry#%3A~%3Atext%3DThe20Growth20of20Autonomous20Technology%26text%3DMost20modern20cars20feature20autonomous%2Cand20work20out20potential20collisions)
2. Autopilot and Full Self-Driving Capability; 2019. Available from: <https://cvpr2021.wad.vision/>.
3. Zheng L, Ismail K, Meng X. Traffic conflict techniques for road safety analysis: open questions and some insights. Canadian journal of civil engineering. 2014;41(7):633-41.
4. Waymo is opening its fully driverless service to the general public in Phoenix; 2020. Available from: [https:](https://blog.waymo.com/2020/10/waymo-is-opening-its-fully-driverless.html)

[//blog.waymo.com/2020/10/waymo-is-opening-its-fully-driverless.html](https://blog.waymo.com/2020/10/waymo-is-opening-its-fully-driverless.html).

1. Seeking NHTSA review of the Origin; 2022. Available from: [https://www.getcruise.com/news/seeki](https://www.getcruise.com/news/seeking-nhtsa-review-of-the-origin) [ng-nhtsa-review-of-the-origin](https://www.getcruise.com/news/seeking-nhtsa-review-of-the-origin).
2. Revealing Zoox to the world; 2020. Available from: [https://zoox.com/journal/revealing-zoox-to-t](https://zoox.com/journal/revealing-zoox-to-the-world/) [he-world/](https://zoox.com/journal/revealing-zoox-to-the-world/).
3. The future of delivery, today; 2020. Available from: <https://www.starship.xyz/business/>.
4. Introducing Our Next-Generation Nuro; 2022. Available from: [https://medium.com/nuro/introducing-](https://medium.com/nuro/introducing-our-next-generation-nuro-8c1c63488342) [our-next-generation-nuro-8c1c63488342](https://medium.com/nuro/introducing-our-next-generation-nuro-8c1c63488342).
5. Tesla Semi; 2022. Available from: <https://www.tesla.com/semi>.
6. Waymo Via and Uber Freight partner to accelerate the future of logistics; 2022. Available from: [https:](https://blog.waymo.com/2022/06/waymo-via-and-uber-freight-partner-to.html)

[//blog.waymo.com/2022/06/waymo-via-and-uber-freight-partner-to.html](https://blog.waymo.com/2022/06/waymo-via-and-uber-freight-partner-to.html).

1. Advanced Signal Control; 2020. Available from: [https://www.flir.com/traffic/incident-detectio](https://www.flir.com/traffic/incident-detection/) [n/](https://www.flir.com/traffic/incident-detection/).
2. Traffic Intelligence from Video; 2016. Available from: <http://www.trafficvision.com/>.
3. Advanced Signal Control; 2020. Available from: [https://www.flir.com/traffic/advanced-signal-c](https://www.flir.com/traffic/advanced-signal-control/) [ontrol/](https://www.flir.com/traffic/advanced-signal-control/).
4. NoTraffic digitizes road infrastructure management, allowing cities to manage their entire grid at the push of a button; 2020. Available from: <https://notraffic.tech/how-it-works/>.
5. Lee WH, Chiu CY. Design and implementation of a smart traffic signal control system for smart city applica- tions. Sensors. 2020;20(2):508.
6. SMARTMICRO SENSORS FOR TRAFFIC MANAGEMENT; 2019. Available from: [https://www.smartm](https://www.smartmicro.com/traffic-sensor#c100) [icro.com/traffic-sensor#c100](https://www.smartmicro.com/traffic-sensor#c100).
7. Hu L, Ou J, Huang J, Chen Y, Cao D. A review of research on traffic conflicts based on intelligent vehicles. Ieee Access. 2020;8:24471-83.
8. Mozaffari S, Al-Jarrah OY, Dianati M, Jennings P, Mouzakitis A. Deep learning-based vehicle behavior predic- tion for autonomous driving applications: A review. IEEE Transactions on Intelligent Transportation Systems. 2020.
9. Grigorescu S, Trasnea B, Cocias T, Macesanu G. A survey of deep learning techniques for autonomous driving. Journal of Field Robotics. 2020;37(3):362-86.
10. Yurtsever E, Lambert J, Carballo A, Takeda K. A survey of autonomous driving: Common practices and emerging technologies. IEEE Access. 2020;8:58443-69.
11. Janai J, Güney F, Behl A, Geiger A, et al. Computer vision for autonomous vehicles: Problems, datasets and state of the art. Foundations and Trends® in Computer Graphics and Vision. 2020;12(1–3):1-308.
12. Badue C, Guidolini R, Carneiro RV, Azevedo P, Cardoso VB, Forechi A, et al. Self-driving cars: A survey. Expert Systems with Applications. 2020:113816.
13. Kumaran SK, Dogra DP, Roy PP. Anomaly detection in road traffic using visual surveillance: A survey. arXiv preprint arXiv:190108292. 2019.
14. Wang Y, Zhang D, Liu Y, Dai B, Lee LH. Enhancing transportation systems via deep learning: A survey. Transportation research part C: emerging technologies. 2019;99:144-63.
15. Nguyen H, Kieu LM, Wen T, Cai C. Deep learning methods in transportation domain: a review. IET Intelligent Transport Systems. 2018;12(9):998-1004.
16. Shirazi MS, Morris BT. Looking at intersections: a survey of intersection monitoring, behavior and safety analysis of recent studies. IEEE Transactions on Intelligent Transportation Systems. 2016;18(1):4-24.
17. Mukhtar A, Xia L, Tang TB. Vehicle detection techniques for collision avoidance systems: A review. IEEE Transactions on Intelligent Transportation Systems. 2015;16(5):2318-38.
18. Morris BT, Trivedi M. Understanding vehicular traffic behavior from video: a survey of unsupervised ap- proaches. Journal of Electronic Imaging. 2013;22(4):041113.
19. LeCun Y, Bengio Y, Hinton G. Deep learning. nature. 2015;521(7553):436-44.
20. Goodfellow I, Bengio Y, Courville A. Deep learning. MIT press; 2016.
21. ;. Available from: [https://www.affectiva.com/product/affectiva-automotive-ai-for-driver-m](https://www.affectiva.com/product/affectiva-automotive-ai-for-driver-monitoring-solutions/) [onitoring-solutions/](https://www.affectiva.com/product/affectiva-automotive-ai-for-driver-monitoring-solutions/).
22. Mejia N. AI in the Automotive Industry - an Analysis of the Space; 2020. Available from: [https://emerj.](https://emerj.com/ai-sector-overviews/ai-in-the-automotive-industry-an-analysis-of-the-space/) [com/ai-sector-overviews/ai-in-the-automotive-industry-an-analysis-of-the-space/](https://emerj.com/ai-sector-overviews/ai-in-the-automotive-industry-an-analysis-of-the-space/).
23. GPS Accuracy;. Available from: <https://www.gps.gov/systems/gps/performance/accuracy/>.
24. Verizon Launches Hyper-Precise GPS Location Technology; 2020. Available from: [https:](https://www.rrmediagroup.com/News/NewsDetails/NewsID/19972#%3A~%3Atext%3DBy%20creating%20a%20vehicle-to%2Cand%20warn%20vehicles%20of%20impending)

[//www.rrmediagroup.com/News/NewsDetails/NewsID/19972#:~:text=Bycreatingavehicle-](https://www.rrmediagroup.com/News/NewsDetails/NewsID/19972#%3A~%3Atext%3DBy%20creating%20a%20vehicle-to%2Cand%20warn%20vehicles%20of%20impending) [to,andwarnvehiclesofimpending](https://www.rrmediagroup.com/News/NewsDetails/NewsID/19972#%3A~%3Atext%3DBy%20creating%20a%20vehicle-to%2Cand%20warn%20vehicles%20of%20impending).

1. Munoz-Ferreras JM, Perez-Martinez F, Calvo-Gallego J, Asensio-Lopez A, Dorta-Naranjo BP, Blanco-del Campo A. Traffic surveillance system based on a high-resolution radar. IEEE transactions on geoscience and remote sensing. 2008;46(6):1624-33.
2. Bilik I, Longman O, Villeval S, Tabrikian J. The rise of radar for autonomous vehicles: Signal processing solutions and future research directions. IEEE signal processing Magazine. 2019;36(5):20-31.
3. Tan M, Wang B, Wu Z, Wang J, Pan G. Weakly supervised metric learning for traffic sign recognition in a LIDAR-equipped vehicle. IEEE Transactions on Intelligent Transportation Systems. 2016;17(5):1415-27.
4. Ma L, Li Y, Li J, Wang C, Wang R, Chapman MA. Mobile laser scanned point-clouds for road object detection and extraction: A review. Remote Sensing. 2018;10(10):1531.
5. Erichsen S, Nitsch J, Schmidt M, Schlaefer A. Semantic segmentation of solid state LiDAR measurements for automotive applications. In: 20. Internationales Stuttgarter Symposium. Springer; 2020. p. 179-92.
6. Khan MA, Ectors W, Bellemans T, Janssens D, Wets G. UAV-based traffic analysis: A universal guiding framework based on literature survey. Transportation research procedia. 2017;22:541-50.
7. Ke R, Li Z, Tang J, Pan Z, Wang Y. Real-time traffic flow parameter estimation from UAV video based on ensemble classifier and optical flow. IEEE Transactions on Intelligent Transportation Systems. 2018;20(1):54- 64.
8. Barmpounakis E, Geroliminis N. On the new era of urban traffic monitoring with massive drone data: The pNEUMA large-scale field experiment. Transportation research part C: emerging technologies. 2020;111:50- 71.
9. Ahmed SA, Hussain T, Saadawi TN. Active and passive infrared sensors for vehicular traffic control. In: Proceedings of IEEE Vehicular Technology Conference (VTC). IEEE; 1994. p. 1393-7.
10. Mimbela LEY, Klein LA, et al. Summary of vehicle detection and surveillance technologies used in intelligent transportation systems. 2007.
11. Zhang J, Lu Y, Lu Z, Liu C, Sun G, Li Z. A new smart traffic monitoring method using embedded cement-based piezoelectric sensors. Smart Materials and Structures. 2015;24(2):025023.
12. Interactive Environmental Sensor Station Page;. Available from: [https://ops.fhwa.dot.gov/weather/m](https://ops.fhwa.dot.gov/weather/mitigating_impacts/interactive_ess.htm) [itigating\_impacts/interactive\_ess.htm](https://ops.fhwa.dot.gov/weather/mitigating_impacts/interactive_ess.htm).
13. Andrej Karpathy (Tesla): CVPR 2021 workshop on autonomous vehicles;. Available from: [https://cvpr20](https://cvpr2021.wad.vision/) [21.wad.vision/](https://cvpr2021.wad.vision/).
14. Fayyad J, Jaradat MA, Gruyer D, Najjaran H. Deep learning sensor fusion for autonomous vehicle perception and localization: A review. Sensors. 2020;20(15):4220.
15. Agustsson E, Timofte R. Ntire 2017 challenge on single image super-resolution: Dataset and study. In: Pro- ceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops; 2017. p. 126-35.
16. Fujimoto A, Ogawa T, Yamamoto K, Matsui Y, Yamasaki T, Aizawa K. Manga109 dataset and creation of metadata. In: Proceedings of the 1st international workshop on comics analysis, processing and understanding; 2016. p. 1-5.
17. Blau Y, Mechrez R, Timofte R, Michaeli T, Zelnik-Manor L. The 2018 pirm challenge on perceptual image super-resolution. In: Proceedings of the European Conference on Computer Vision (ECCV); 2018. p. 0-0.
18. Huang JB, Singh A, Ahuja N. Single image super-resolution from transformed self-exemplars. In: Proceedings of the IEEE conference on computer vision and pattern recognition; 2015. p. 5197-206.
19. Cai J, Zeng H, Yong H, Cao Z, Zhang L. Toward real-world single image super-resolution: A new benchmark and a new model. In: Proceedings of the IEEE International Conference on Computer Vision; 2019. p. 3086-95.
20. Wang Z, Chen J, Hoi SC. Deep learning for image super-resolution: A survey. IEEE transactions on pattern analysis and machine intelligence. 2020.
21. Suresh KV, Kumar GM, Rajagopalan AN. Superresolution of License Plates in Real Traffic Videos. IEEE Transactions on Intelligent Transportation Systems. 2007;8(2):321-31.
22. Zeng W, Lu X. A Generalized DAMRF Image Modeling for Superresolution of License Plates. IEEE Transac- tions on Intelligent Transportation Systems. 2012;13(2):828-37.
23. Song BC, Jeong S, Choi Y. Video Super-Resolution Algorithm Using Bi-Directional Overlapped Block Motion Compensation and On-the-Fly Dictionary Training. IEEE Transactions on Circuits and Systems for Video Technology. 2011;21(3):274-85.
24. Yang J, Wright J, Huang TS, Ma Y. Image super-resolution via sparse representation. IEEE transactions on image processing. 2010;19(11):2861-73.
25. Dong W, Zhang L, Shi G, Wu X. Image deblurring and super-resolution by adaptive sparse domain selection and adaptive regularization. IEEE Transactions on image processing. 2011;20(7):1838-57.
26. Zhang D, Du M. Super-resolution image reconstruction via adaptive sparse representation and joint dictionary training. In: 2013 6th International Congress on Image and Signal Processing (CISP). vol. 1. IEEE; 2013. p. 516-21.
27. Vasek V, Franc V, Urban M. License Plate Recognition and Super-resolution from Low-Resolution Videos by Convolutional Neural Networks. In: BMVC; 2018. p. 132.
28. Liu W, Liu X, Ma H, Cheng P. Beyond human-level license plate super-resolution with progressive vehicle search and domain priori GAN. In: Proceedings of the 25th ACM international conference on Multimedia; 2017. p. 1618-26.
29. Lee Y, Yun J, Hong Y, Lee J, Jeon M. Accurate License Plate Recognition and Super-Resolution Using a Generative Adversarial Networks on Traffic Surveillance Video. In: 2018 IEEE International Conference on Consumer Electronics - Asia (ICCE-Asia); 2018. p. 1-4.
30. Lee Y, Jun J, Hong Y, Jeon M. Practical License Plate Recognition in Unconstrained Surveillance Systems with Adversarial Super-Resolution. arXiv preprint arXiv:191004324. 2019.
31. Zhang M, Liu W, Ma H. Joint license plate super-resolution and recognition in one multi-task gan framework. In: 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE; 2018. p. 1443-7.
32. Abdelhamed A, Lin S, Brown MS. A High-Quality Denoising Dataset for Smartphone Cameras. In: 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition; 2018. p. 1692-700.
33. Plötz T, Roth S. Benchmarking Denoising Algorithms with Real Photographs. In: 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR); 2017. p. 2750-9.
34. Yuan Z, Xie X, Hu J, Yao D. An Efficient Method for Traffic Image Denoising. Procedia-Social and Behavioral Sciences. 2014;138:439-45.
35. Chakraborty P, Hegde C, Sharma A. Data-driven parallelizable traffic incident detection using spatio-temporally denoised robust thresholds. Transportation research part C: emerging technologies. 2019;105:81-99.
36. Sochor J, Herout A, Havel J. Boxcars: 3d boxes as cnn input for improved fine-grained vehicle recognition. In: Proceedings of the IEEE conference on computer vision and pattern recognition; 2016. p. 3006-15.
37. Sochor J, Španˇhel J, Herout A. Boxcars: Improving fine-grained recognition of vehicles using 3-d bounding boxes in traffic surveillance. IEEE transactions on intelligent transportation systems. 2018;20(1):97-108.
38. Ma Z, Chang D, Xie J, Ding Y, Wen S, Li X, et al. Fine-grained vehicle classification with channel max pooling modified CNNs. IEEE Transactions on Vehicular Technology. 2019;68(4):3224-33.
39. Krause J, Stark M, Deng J, Fei-Fei L. 3d object representations for fine-grained categorization. In: Proceedings of the IEEE international conference on computer vision workshops; 2013. p. 554-61.
40. Yang L, Luo P, Change Loy C, Tang X. A large-scale car dataset for fine-grained categorization and verification. In: Proceedings of the IEEE conference on computer vision and pattern recognition; 2015. p. 3973-81.
41. Li X, Yu L, Chang D, Ma Z, Cao J. Dual cross-entropy loss for small-sample fine-grained vehicle classification. IEEE Transactions on Vehicular Technology. 2019;68(5):4204-12.
42. Xiang Y, Fu Y, Huang H. Global topology constraint network for fine-grained vehicle recognition. IEEE Transactions on Intelligent Transportation Systems. 2019;21(7):2918-29.
43. Huang K, Zhang B. Fine-grained vehicle recognition by deep Convolutional Neural Network. In: 2016 9th In- ternational Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI). IEEE; 2016. p. 465-70.
44. Zhu W, Yu S, Zheng X, Wu Y. Fine-grained Vehicle Classification Technology Based on Fusion of Multi- convolutional Neural Networks. Sensors and Materials. 2019;31(2):569-78.
45. Yu Y, Jin Q, Chen CW. FF-CMnet: A CNN-based model for fine-grained classification of car models based on feature fusion. In: 2018 IEEE International Conference on Multimedia and Expo (ICME). IEEE; 2018. p. 1-6.
46. Yu Y, Xu L, Jia W, Zhu W, Fu Y, Lu Q. CAM: A fine-grained vehicle model recognition method based on visual attention model. Image and Vision Computing. 2020;104:104027.
47. Ke X, Zhang Y. Fine-grained vehicle type detection and recognition based on dense attention network. Neuro- computing. 2020;399:247-57.
48. Hu B, Lai JH, Guo CC. Location-aware fine-grained vehicle type recognition using multi-task deep networks. Neurocomputing. 2017;243:60-8.
49. Wang Q, Teng Z, Xing J, Gao J, Hu W, Maybank S. Learning attentions: residual attentional siamese network for high performance online visual tracking. In: Proceedings of the IEEE conference on computer vision and pattern recognition; 2018. p. 4854-63.
50. Zhang Q, Zhuo L, Zhang S, Li J, Zhang H, Li X. Fine-grained vehicle recognition using lightweight convo- lutional neural network with combined learning strategy. In: 2018 IEEE Fourth International Conference on Multimedia Big Data (BigMM). IEEE; 2018. p. 1-5.
51. Ling Q, Deng S, Li F, Huang Q, Li X. A feedback-based robust video stabilization method for traffic videos. IEEE Transactions on Circuits and Systems for Video Technology. 2016;28(3):561-72.
52. Zhao M, Deng S, Ling Q. A fast traffic video stabilization method based on trajectory derivatives. IEEE Access. 2019;7:13422-32.
53. Tang C, Yang X, Chen L, Zhai G. A fast video stabilization algorithm based on block matching and edge completion. In: 2011 IEEE 13th International Workshop on Multimedia Signal Processing. IEEE; 2011. p. 1-5.
54. Xu L, Lin X. Digital image stabilization based on circular block matching. IEEE Transactions on Consumer Electronics. 2006;52(2):566-74.
55. Kwon O, Shin J, Paik J. Video stabilization using Kalman filter and phase correlation matching. In: International Conference Image Analysis and Recognition. Springer; 2005. p. 141-8.
56. Zhu J, Guo B. Video stabilization with sub-image phase correlation. Chinese Optics Letters. 2006;4(9):553-5.
57. Liu S, Yuan L, Tan P, Sun J. Steadyflow: Spatially smooth optical flow for video stabilization. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition; 2014. p. 4209-16.
58. Chang HC, Lai SH, Lu KR. A robust and efficient video stabilization algorithm. In: 2004 IEEE International Conference on Multimedia and Expo (ICME)(IEEE Cat. No. 04TH8763). vol. 1. IEEE; 2004. p. 29-32.
59. Amisha P, Vala MH. A survey on video stabilization techniques. 2015.
60. Lowe DG. Object recognition from local scale-invariant features. In: Proceedings of the seventh IEEE interna- tional conference on computer vision. vol. 2. Ieee; 1999. p. 1150-7.
61. Bay H, Tuytelaars T, Van Gool L. Surf: Speeded up robust features. In: European conference on computer vision. Springer; 2006. p. 404-17.
62. Wang M, Yang GY, Lin JK, Zhang SH, Shamir A, Lu SP, et al. Deep online video stabilization with multi-grid warping transformation learning. IEEE Transactions on Image Processing. 2018;28(5):2283-92.
63. Xu SZ, Hu J, Wang M, Mu TJ, Hu SM. Deep video stabilization using adversarial networks. In: Computer Graphics Forum. vol. 37. Wiley Online Library; 2018. p. 267-76.
64. Lee KM, Lin CH. Video Stabilization Algorithm of Shaking image using Deep Learning. The Journal of The Institute of Internet, Broadcasting and Communication. 2019;19(1):145-52.
65. Liang YM, Tyan HR, Chang SL, Liao HY, Chen SW. Video stabilization for a camcorder mounted on a moving vehicle. IEEE Transactions on Vehicular Technology. 2004;53(6):1636-48.
66. Zhang Y, Xie M, Tang D. A central sub-image based global motion estimation method for in-car video stabi- lization. In: 2010 Third International Conference on Knowledge Discovery and Data Mining. IEEE; 2010. p. 204-7.
67. Caraffi C, Vojíˇr T, Trefny` J, Šochman J, Matas J. A system for real-time detection and tracking of vehicles from a single car-mounted camera. In: 2012 15th international IEEE conference on intelligent transportation systems. IEEE; 2012. p. 975-82.
68. Outay F, Mengash HA, Adnan M. Applications of unmanned aerial vehicle (UAV) in road safety, traffic and highway infrastructure management: Recent advances and challenges. Transportation research part A: policy and practice. 2020;141:116-29.
69. Liu W, Anguelov D, Erhan D, Szegedy C, Reed S, Fu CY, et al. Ssd: Single shot multibox detector. In: European conference on computer vision. Springer; 2016. p. 21-37.
70. He K, Gkioxari G, Dollár P, Girshick R. Mask r-cnn. In: Proceedings of the IEEE international conference on computer vision; 2017. p. 2961-9.
71. Krizhevsky A, Sutskever I, Hinton GE. Imagenet classification with deep convolutional neural networks. In: Advances in neural information processing systems; 2012. p. 1097-105.
72. Simonyan K, Zisserman A. Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:14091556. 2014.
73. Szegedy C, Liu W, Jia Y, Sermanet P, Reed S, Anguelov D, et al. Going deeper with convolutions. In: Proceed- ings of the IEEE conference on computer vision and pattern recognition; 2015. p. 1-9.
74. He K, Zhang X, Ren S, Sun J. Deep residual learning for image recognition. In: Proceedings of the IEEE conference on computer vision and pattern recognition; 2016. p. 770-8.
75. Howard AG, Zhu M, Chen B, Kalenichenko D, Wang W, Weyand T, et al. Mobilenets: Efficient convolutional neural networks for mobile vision applications. arXiv preprint arXiv:170404861. 2017.
76. Huang G, Liu Z, Van Der Maaten L, Weinberger KQ. Densely connected convolutional networks. In: Proceed- ings of the IEEE conference on computer vision and pattern recognition; 2017. p. 4700-8.
77. Tan M, Le QV. Efficientnet: Rethinking model scaling for convolutional neural networks. arXiv preprint arXiv:190511946. 2019.
78. Shen X. A survey of Object Classification and Detection based on 2D/3D data. arXiv preprint arXiv:190512683. 2019.
79. Schmarje L, Santarossa M, Schröder SM, Koch R. A survey on semi-, self-and unsupervised techniques in image classification. arXiv preprint arXiv:200208721. 2020.
80. Zhao B, Feng J, Wu X, Yan S. A survey on deep learning-based fine-grained object classification and semantic segmentation. International Journal of Automation and Computing. 2017;14(2):119-35.
81. Wang W, Yang Y, Wang X, Wang W, Li J. Development of convolutional neural network and its application in image classification: a survey. Optical Engineering. 2019;58(4):040901.
82. Jocher G, Stoken A, Borovec J, NanoCode012, Chaurasia A, TaoXie, et al.. ultralytics/yolov5: v5.0 - YOLOv5- P6 1280 models, AWS, Supervise.ly and YouTube integrations. Zenodo; 2021. Available from: [https://do](https://doi.org/10.5281/zenodo.4679653) [i.org/10.5281/zenodo.4679653](https://doi.org/10.5281/zenodo.4679653).
83. Ren S, He K, Girshick R, Sun J. Faster r-cnn: Towards real-time object detection with region proposal networks. In: Advances in neural information processing systems; 2015. p. 91-9.
84. Wang M, Wang X. Automatic adaptation of a generic pedestrian detector to a specific traffic scene. In: CVPR 2011. IEEE; 2011. p. 3401-8.
85. Morris BT, Trivedi MM. Trajectory learning for activity understanding: Unsupervised, multilevel, and long- term adaptive approach. IEEE transactions on pattern analysis and machine intelligence. 2011;33(11):2287-301.
86. Hospedales T, Gong S, Xiang T. Video behaviour mining using a dynamic topic model. International journal of computer vision. 2012;98(3):303-23.
87. Viola P, Jones M. Rapid object detection using a boosted cascade of simple features. In: Proceedings of the 2001 IEEE computer society conference on computer vision and pattern recognition. CVPR 2001. vol. 1. IEEE; 2001. p. I-I.
88. Dalal N, Triggs B. Histograms of oriented gradients for human detection. In: 2005 IEEE computer society conference on computer vision and pattern recognition (CVPR’05). vol. 1. IEEE; 2005. p. 886-93.
89. Felzenszwalb PF, Girshick RB, McAllester D, Ramanan D. Object detection with discriminatively trained part-based models. IEEE transactions on pattern analysis and machine intelligence. 2009;32(9):1627-45.
90. Girshick R, Donahue J, Darrell T, Malik J. Rich feature hierarchies for accurate object detection and semantic segmentation. In: Proceedings of the IEEE conference on computer vision and pattern recognition; 2014. p. 580-7.
91. Girshick R. Fast r-cnn. In: Proceedings of the IEEE international conference on computer vision; 2015. p. 1440-8.
92. Dai J, Li Y, He K, Sun J. R-fcn: Object detection via region-based fully convolutional networks. In: Advances in neural information processing systems; 2016. p. 379-87.
93. Pang J, Chen K, Shi J, Feng H, Ouyang W, Lin D. Libra r-cnn: Towards balanced learning for object detection. In: Proceedings of the IEEE conference on computer vision and pattern recognition; 2019. p. 821-30.
94. Uijlings JR, Van De Sande KE, Gevers T, Smeulders AW. Selective search for object recognition. International journal of computer vision. 2013;104(2):154-71.
95. He K, Zhang X, Ren S, Sun J. Spatial pyramid pooling in deep convolutional networks for visual recognition. IEEE transactions on pattern analysis and machine intelligence. 2015;37(9):1904-16.
96. Redmon J, Farhadi A. YOLO9000: better, faster, stronger. In: Proceedings of the IEEE conference on computer vision and pattern recognition; 2017. p. 7263-71.
97. Redmon J, Farhadi A. Yolov3: An incremental improvement. arXiv preprint arXiv:180402767. 2018.
98. Bochkovskiy A, Wang CY, Liao HYM. YOLOv4: Optimal Speed and Accuracy of Object Detection. arXiv preprint arXiv:200410934. 2020.
99. Huang L, Yang Y, Deng Y, Yu Y. Densebox: Unifying landmark localization with end to end object detection. arXiv preprint arXiv:150904874. 2015.
100. Tian Z, Shen C, Chen H, He T. Fcos: Fully convolutional one-stage object detection. In: Proceedings of the IEEE international conference on computer vision; 2019. p. 9627-36.
101. Lin TY, Goyal P, Girshick R, He K, Dollár P. Focal loss for dense object detection. In: Proceedings of the IEEE international conference on computer vision; 2017. p. 2980-8.
102. Law H, Deng J. Cornernet: Detecting objects as paired keypoints. In: Proceedings of the European Conference on Computer Vision (ECCV); 2018. p. 734-50.
103. Law H, Teng Y, Russakovsky O, Deng J. Cornernet-lite: Efficient keypoint based object detection. arXiv preprint arXiv:190408900. 2019.
104. Zhou X, Wang D, Krähenbühl P. Objects as points. arXiv preprint arXiv:190407850. 2019.
105. Duan K, Bai S, Xie L, Qi H, Huang Q, Tian Q. Centernet: Keypoint triplets for object detection. In: Proceedings of the IEEE International Conference on Computer Vision; 2019. p. 6569-78.
106. Zhou X, Zhuo J, Krahenbuhl P. Bottom-up object detection by grouping extreme and center points. In: Pro- ceedings of the IEEE Conference on Computer Vision and Pattern Recognition; 2019. p. 850-9.
107. Chen X, Xiang S, Liu C, Pan C. Vehicle Detection in Satellite Images by Hybrid Deep Convolutional Neural Networks. IEEE Geoscience and Remote Sensing Letters. 2014;11(10):1797-801.
108. Wang L, Lu Y, Wang H, Zheng Y, Ye H, Xue X. Evolving boxes for fast vehicle detection. In: 2017 IEEE International Conference on Multimedia and Expo (ICME); 2017. p. 1135-40.
109. Kim S, Jeon H, Koo H. Deep-learning-based license plate detection method using vehicle region extraction. Electronics Letters. 2017;53(15):1034-6.
110. Selmi Z, Halima MB, Alimi AM. Deep learning system for automatic license plate detection and recognition. In: 2017 14th IAPR international conference on document analysis and recognition (ICDAR). vol. 1. IEEE; 2017. p. 1132-8.
111. Masood SZ, Shu G, Dehghan A, Ortiz EG. License plate detection and recognition using deeply learned convolutional neural networks. arXiv preprint arXiv:170307330. 2017.
112. Xiao Y, Zhou K, Cui G, Jia L, Fang Z, Yang X, et al. Deep learning for occluded and multi-scale pedestrian detection: A review. Iet Image Processing. 2021;15(2):286-301.
113. Cai Z, Fan Q, Feris RS, Vasconcelos N. A unified multi-scale deep convolutional neural network for fast object detection. In: European conference on computer vision. Springer; 2016. p. 354-70.
114. Li J, Liang X, Shen S, Xu T, Feng J, Yan S. Scale-aware fast R-CNN for pedestrian detection. IEEE transactions on Multimedia. 2017;20(4):985-96.
115. Lin C, Lu J, Wang G, Zhou J. Graininess-aware deep feature learning for pedestrian detection. In: Proceedings of the European conference on computer vision (ECCV); 2018. p. 732-47.
116. Zhou C, Wu M, Lam SK. SSA-CNN: Semantic self-attention CNN for pedestrian detection. arXiv preprint arXiv:190209080. 2019.
117. Tian Y, Luo P, Wang X, Tang X. Deep learning strong parts for pedestrian detection. In: Proceedings of the IEEE international conference on computer vision; 2015. p. 1904-12.
118. Xie J, Pang Y, Cholakkal H, Anwer R, Khan F, Shao L. PSC-Net: learning part spatial co-occurrence for occluded pedestrian detection. Science China Information Sciences. 2021;64(2):1-13.
119. Wang S, Cheng J, Liu H, Tang M. Pcn: Part and context information for pedestrian detection with cnns. arXiv preprint arXiv:180404483. 2018.
120. Liu W, Liao S, Ren W, Hu W, Yu Y. High-level semantic feature detection: A new perspective for pedestrian detection. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition; 2019. p. 5187-96.
121. Chi C, Zhang S, Xing J, Lei Z, Li SZ, Zou X. Pedhunter: Occlusion robust pedestrian detector in crowded scenes. In: Proceedings of the AAAI Conference on Artificial Intelligence. vol. 34; 2020. p. 10639-46.
122. Luo Y, Zhang C, Zhao M, Zhou H, Sun J. Where, What, Whether: Multi-modal learning meets pedestrian detection. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition; 2020. p. 14065-73.
123. Zhu JY, Park T, Isola P, Efros AA. Unpaired image-to-image translation using cycle-consistent adversarial networks. In: Proceedings of the IEEE international conference on computer vision; 2017. p. 2223-32.
124. Dollar P, Wojek C, Schiele B, Perona P. Pedestrian detection: An evaluation of the state of the art. IEEE transactions on pattern analysis and machine intelligence. 2011;34(4):743-61.
125. Geiger A, Lenz P, Urtasun R. Are we ready for Autonomous Driving? The KITTI Vision Benchmark Suite. In: Conference on Computer Vision and Pattern Recognition (CVPR); 2012. .
126. Hwang S, Park J, Kim N, Choi Y, So Kweon I. Multispectral pedestrian detection: Benchmark dataset and baseline. In: Proceedings of the IEEE conference on computer vision and pattern recognition; 2015. p. 1037- 45.
127. Hu Q, Wang P, Shen C, van den Hengel A, Porikli F. Pushing the limits of deep CNNs for pedestrian detection. IEEE Transactions on Circuits and Systems for Video Technology. 2017;28(6):1358-68.
128. Liu J, Zhang S, Wang S, Metaxas DN. Multispectral deep neural networks for pedestrian detection. arXiv preprint arXiv:161102644. 2016.
129. Zhang L, Liu Z, Zhang S, Yang X, Qiao H, Huang K, et al. Cross-modality interactive attention network for multispectral pedestrian detection. Information Fusion. 2019;50:20-9.
130. Li C, Song D, Tong R, Tang M. Illumination-aware faster R-CNN for robust multispectral pedestrian detection. Pattern Recognition. 2019;85:161-71.
131. Zhou K, Chen L, Cao X. Improving multispectral pedestrian detection by addressing modality imbalance problems. In: European Conference on Computer Vision. Springer; 2020. p. 787-803.
132. Zhang L, Zhu X, Chen X, Yang X, Lei Z, Liu Z. Weakly aligned cross-modal learning for multispectral pedestrian detection. In: Proceedings of the IEEE/CVF International Conference on Computer Vision; 2019. p. 5127-37.
133. González A, Fang Z, Socarras Y, Serrat J, Vázquez D, Xu J, et al. Pedestrian detection at day/night time with visible and FIR cameras: A comparison. Sensors. 2016;16(6):820.
134. Espinosa JE, Velastin SA, Branch JW. Vehicle detection using alex net and faster R-CNN deep learning models: a comparative study. In: International Visual Informatics Conference. Springer; 2017. p. 3-15.
135. Wang L, Lu Y, Wang H, Zheng Y, Ye H, Xue X. Evolving boxes for fast vehicle detection. In: 2017 IEEE international conference on multimedia and Expo (ICME). IEEE; 2017. p. 1135-40.
136. Soin A, Chahande M. Moving vehicle detection using deep neural network. In: 2017 International Conference on Emerging Trends in Computing and Communication Technologies (ICETCCT). IEEE; 2017. p. 1-5.
137. Zhang JS, Cao J, Mao B. Application of deep learning and unmanned aerial vehicle technology in traffic flow monitoring. In: 2017 International Conference on Machine Learning and Cybernetics (ICMLC). vol. 1. IEEE; 2017. p. 189-94.
138. Peppa M, Bell D, Komar T, Xiao W. URBAN TRAFFIC FLOW ANALYSIS BASED ON DEEP LEARNING CAR DETECTION FROM CCTV IMAGE SERIES. International Archives of the Photogrammetry, Remote Sensing & Spatial Information Sciences. 2018;42(4).
139. Yu S, Wu Y, Li W, Song Z, Zeng W. A model for fine-grained vehicle classification based on deep learning. Neurocomputing. 2017;257:97-103.
140. Wen L, Du D, Cai Z, Lei Z, Chang MC, Qi H, et al. UA-DETRAC: A new benchmark and protocol for multi- object detection and tracking. arXiv preprint arXiv:151104136. 2015.
141. Sang J, Wu Z, Guo P, Hu H, Xiang H, Zhang Q, et al. An improved YOLOv2 for vehicle detection. Sensors. 2018;18(12):4272.
142. Kim KJ, Kim PK, Chung YS, Choi DH. Multi-scale detector for accurate vehicle detection in traffic surveillance data. IEEE Access. 2019;7:78311-9.
143. Kasper-Eulaers M, Hahn N, Berger S, Sebulonsen T, Myrland Ø, Kummervold PE. Detecting Heavy Goods Vehicles in Rest Areas in Winter Conditions Using YOLOv5. Algorithms. 2021;14(4):114.
144. Nayak A, Gopalswamy S, Rathinam S. Vision-based techniques for identifying emergency vehicles. SAE Technical Paper; 2019.
145. Zhang F, Li C, Yang F. Vehicle detection in urban traffic surveillance images based on convolutional neural networks with feature concatenation. Sensors. 2019;19(3):594.
146. Chen W, Qiao Y, Li Y. Inception-SSD: An improved single shot detector for vehicle detection. Journal of Ambient Intelligence and Humanized Computing. 2020:1-7.
147. Cao J, Song C, Song S, Peng S, Wang D, Shao Y, et al. Front vehicle detection algorithm for smart car based on improved SSD model. Sensors. 2020;20(16):4646.
148. Zhou Y, Liu L, Shao L, Mellor M. DAVE: A unified framework for fast vehicle detection and annotation. In: European Conference on Computer Vision. Springer; 2016. p. 278-93.
149. Everingham M, Van Gool L, Williams CK, Winn J, Zisserman A. The pascal visual object classes (voc) chal- lenge. International journal of computer vision. 2010;88(2):303-38.
150. Sivaraman S, Trivedi MM. A general active-learning framework for on-road vehicle recognition and tracking. IEEE Transactions on Intelligent Transportation Systems. 2010;11(2):267-76.
151. Lee D, Yoon S, Lee J, Park DS. Real-time license plate detection based on faster R-CNN. KIPS Transactions on Software and Data Engineering. 2016;5(11):511-20.
152. Kessentini Y, Besbes MD, Ammar S, Chabbouh A. A two-stage deep neural network for multi-norm license plate detection and recognition. Expert Systems with Applications. 2019;136:159-70.
153. Khazaee S, Tourani A, Soroori S, Shahbahrami A, Suen CY. A Real-Time License Plate Detection Method Us- ing a Deep Learning Approach. In: International Conference on Pattern Recognition and Artificial Intelligence. Springer; 2020. p. 425-38.
154. Xie L, Ahmad T, Jin L, Liu Y, Zhang S. A new CNN-based method for multi-directional car license plate detection. IEEE Transactions on Intelligent Transportation Systems. 2018;19(2):507-17.
155. Chen RC, et al. Automatic License Plate Recognition via sliding-window darknet-YOLO deep learning. Image and Vision Computing. 2019;87:47-56.
156. GAP-LP Dataset;. Available from: <https://sites.google.com/site/matdbparking/>.
157. Yuan Y, Zou W, Zhao Y, Wang X, Hu X, Komodakis N. A robust and efficient approach to license plate detection. IEEE Transactions on Image Processing. 2016;26(3):1102-14.
158. Ren J, Li H. Implementation of Vehicle and License Plate Detection on Embedded Platform. In: 2020 12th International Conference on Measuring Technology and Mechatronics Automation (ICMTMA). IEEE; 2020. p. 75-9.
159. Hu X, Li H, Li X, Wang C. MobileNet-SSD MicroScope using adaptive error correction algorithm: real-time detection of license plates on mobile devices. IET Intelligent Transport Systems. 2020;14(2):110-8.
160. Danilenko A. License plate detection and recognition using convolution networks. In: 2020 International Conference on Information Technology and Nanotechnology (ITNT). IEEE; 2020. p. 1-6.
161. ;. Available from: <http://www.vision.caltech.edu/archive.html>.
162. openalpr/benchmarks;. Available from: [https://github.com/openalpr/benchmarks/tree/master/end](https://github.com/openalpr/benchmarks/tree/master/endtoend/us) [toend/us](https://github.com/openalpr/benchmarks/tree/master/endtoend/us).
163. Qian R, Liu Q, Yue Y, Coenen F, Zhang B. Road surface traffic sign detection with hybrid region proposal and fast R-CNN. In: 2016 12th International Conference on Natural Computation, Fuzzy Systems and Knowledge Discovery (ICNC-FSKD). IEEE; 2016. p. 555-9.
164. Shao F, Wang X, Meng F, Zhu J, Wang D, Dai J. Improved faster R-CNN traffic sign detection based on a second region of interest and highly possible regions proposal network. Sensors. 2019;19(10):2288.
165. Zhang J, Xie Z, Sun J, Zou X, Wang J. A cascaded R-CNN with multiscale attention and imbalanced samples for traffic sign detection. IEEE Access. 2020;8:29742-54.
166. Zuo Z, Yu K, Zhou Q, Wang X, Li T. Traffic signs detection based on faster r-cnn. In: 2017 IEEE 37th International Conference on Distributed Computing Systems Workshops (ICDCSW). IEEE; 2017. p. 286-8.
167. Wu L, Li H, He J, Chen X. Traffic sign detection method based on Faster R-CNN. In: Journal of Physics: Conference Series. vol. 1176. IOP Publishing; 2019. p. 032045.
168. Peng E, Chen F, Song X. Traffic sign detection with convolutional neural networks. In: International Conference on Cognitive Systems and Signal Processing. Springer; 2016. p. 214-24.
169. Yang Y, Luo H, Xu H, Wu F. Towards real-time traffic sign detection and classification. IEEE Transactions on Intelligent transportation systems. 2015;17(7):2022-31.
170. Zhang J, Huang M, Jin X, Li X. A real-time chinese traffic sign detection algorithm based on modified YOLOv2. Algorithms. 2017;10(4):127.
171. Tai SK, Dewi C, Chen RC, Liu YT, Jiang X, Yu H. Deep Learning for Traffic Sign Recognition Based on Spatial Pyramid Pooling with Scale Analysis. Applied Sciences. 2020 Oct;10(19):6997. Available from: [http:](http://dx.doi.org/10.3390/app10196997)

[//dx.doi.org/10.3390/app10196997](http://dx.doi.org/10.3390/app10196997).

1. Liu W, Wang Z, Zhou B, Yang S, Gong Z. Real-time Signal Light Detection based on Yolov5 for Railway. In: IOP Conference Series: Earth and Environmental Science. vol. 769. IOP Publishing; 2021. p. 042069.
2. Qin Z, Yan WQ. Traffic-sign recognition using deep learning. In: Geometry and Vision: First International Symposium, ISGV 2021, Auckland, New Zealand, January 28-29, 2021, Revised Selected Papers 1. Springer; 2021. p. 13-25.
3. Gao B, Jiang Z, zhang J. Traffic Sign Detection based on SSD. In: Proceedings of the 2019 4th International Conference on Automation, Control and Robotics Engineering; 2019. p. 1-6.
4. You S, Bi Q, Ji Y, Liu S, Feng Y, Wu F. Traffic Sign Detection Method Based on Improved SSD. Information. 2020;11(10):475.
5. Zhu Z, Liang D, Zhang S, Huang X, Li B, Hu S. Traffic-sign detection and classification in the wild. In: Proceedings of the IEEE conference on computer vision and pattern recognition; 2016. p. 2110-8.
6. Wu Y, Liu Y, Li J, Liu H, Hu X. Traffic sign detection based on convolutional neural networks. In: The 2013 international joint conference on neural networks (IJCNN). IEEE; 2013. p. 1-7.
7. Shustanov A, Yakimov P. CNN design for real-time traffic sign recognition. Procedia engineering. 2017;201:718-25.
8. Zhang S, Wen L, Bian X, Lei Z, Li SZ. Occlusion-aware R-CNN: detecting pedestrians in a crowd. In: Proceedings of the European Conference on Computer Vision (ECCV); 2018. p. 637-53.
9. Liu M, Zhu C, Wang J, Yin XC. Adaptive Pattern-Parameter Matching for Robust Pedestrian Detection. In: Proceedings of the AAAI Conference on Artificial Intelligence. vol. 35; 2021. p. 2154-62.
10. Guan D, Cao Y, Yang J, Cao Y, Yang MY. Fusion of multispectral data through illumination-aware deep neural networks for pedestrian detection. Information Fusion. 2019;50:148-57.
11. Kim JU, Park S, Ro YM. Robust small-scale pedestrian detection with cued recall via memory learning. In: Proceedings of the IEEE/CVF International Conference on Computer Vision; 2021. p. 3050-9.
12. Kim JU, Park S, Ro YM. Uncertainty-guided cross-modal learning for robust multispectral pedestrian detection. IEEE Transactions on Circuits and Systems for Video Technology. 2021.
13. Jiang Q, Dai J, Rui T, Shao F, Wang J, Lu G. Attention-Based Cross-Modality Feature Complementation for Multispectral Pedestrian Detection. IEEE Access. 2022.
14. Menze M, Geiger A. Object scene flow for autonomous vehicles. In: Proceedings of the IEEE conference on computer vision and pattern recognition; 2015. p. 3061-70.
15. Fiaz M, Mahmood A, Javed S, Jung SK. Handcrafted and deep trackers: Recent visual object tracking ap- proaches and trends. ACM Computing Surveys (CSUR). 2019;52(2):1-44.
16. Hare S, Golodetz S, Saffari A, Vineet V, Cheng MM, Hicks SL, et al. Struck: Structured output tracking with kernels. IEEE transactions on pattern analysis and machine intelligence. 2015;38(10):2096-109.
17. Wang X, Hua G, Han TX. Discriminative tracking by metric learning. In: European conference on computer vision. Springer; 2010. p. 200-14.
18. Kalal Z, Matas J, Mikolajczyk K. Pn learning: Bootstrapping binary classifiers by structural constraints. In: 2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition. IEEE; 2010. p. 49-56.
19. Wang Q, Chen F, Xu W, Yang MH. Object tracking with joint optimization of representation and classification. IEEE Transactions on Circuits and Systems for Video Technology. 2014;25(4):638-50.
20. Kwon J, Lee KM. Tracking by sampling trackers. In: 2011 International Conference on Computer Vision. IEEE; 2011. p. 1195-202.
21. Sevilla-Lara L, Learned-Miller E. Distribution fields for tracking. In: 2012 IEEE Conference on computer vision and pattern recognition. IEEE; 2012. p. 1910-7.
22. Liu T, Wang G, Wang L, Chan KL. Visual tracking via temporally smooth sparse coding. IEEE Signal Process- ing Letters. 2014;22(9):1452-6.
23. Belagiannis V, Schubert F, Navab N, Ilic S. Segmentation based particle filtering for real-time 2d object tracking. In: European Conference on Computer Vision. Springer; 2012. p. 842-55.
24. Kwak S, Nam W, Han B, Han JH. Learning occlusion with likelihoods for visual tracking. In: 2011 International Conference on Computer Vision. IEEE; 2011. p. 1551-8.
25. Bolme DS, Beveridge JR, Draper BA, Lui YM. Visual object tracking using adaptive correlation filters. In: 2010 IEEE computer society conference on computer vision and pattern recognition. IEEE; 2010. p. 2544-50.
26. Bolme DS, Draper BA, Beveridge JR. Average of synthetic exact filters. In: 2009 IEEE Conference on Com- puter Vision and Pattern Recognition. IEEE; 2009. p. 2105-12.
27. Henriques JF, Caseiro R, Martins P, Batista J. Exploiting the circulant structure of tracking-by-detection with kernels. In: European conference on computer vision. Springer; 2012. p. 702-15.
28. Henriques JF, Caseiro R, Martins P, Batista J. High-speed tracking with kernelized correlation filters. IEEE transactions on pattern analysis and machine intelligence. 2014;37(3):583-96.
29. Kiani Galoogahi H, Fagg A, Lucey S. Learning background-aware correlation filters for visual tracking. In: Proceedings of the IEEE international conference on computer vision; 2017. p. 1135-43.
30. Li Y, Zhu J. A scale adaptive kernel correlation filter tracker with feature integration. In: European conference on computer vision. Springer; 2014. p. 254-65.
31. Bewley A, Ge Z, Ott L, Ramos F, Upcroft B. Simple online and realtime tracking. In: 2016 IEEE International Conference on Image Processing (ICIP). IEEE; 2016. p. 3464-8.
32. Yu F, Li W, Li Q, Liu Y, Shi X, Yan J. Poi: Multiple object tracking with high performance detection and appearance feature. In: European Conference on Computer Vision. Springer; 2016. p. 36-42.
33. Wojke N, Bewley A, Paulus D. Simple online and realtime tracking with a deep association metric. In: 2017 IEEE international conference on image processing (ICIP). IEEE; 2017. p. 3645-9.
34. Zhao D, Fu H, Xiao L, Wu T, Dai B. Multi-object tracking with correlation filter for autonomous vehicle. Sensors. 2018;18(7):2004.
35. Lu Y, Lu C, Tang CK. Online video object detection using association LSTM. In: Proceedings of the IEEE International Conference on Computer Vision; 2017. p. 2344-52.
36. Fang K, Xiang Y, Li X, Savarese S. Recurrent autoregressive networks for online multi-object tracking. In: 2018 IEEE Winter Conference on Applications of Computer Vision (WACV). IEEE; 2018. p. 466-75.
37. Maksai A, Fua P. Eliminating exposure bias and loss-evaluation mismatch in multiple object tracking. arXiv preprint arXiv:181110984. 2018.
38. Zhu J, Yang H, Liu N, Kim M, Zhang W, Yang MH. Online multi-object tracking with dual matching attention networks. In: Proceedings of the European Conference on Computer Vision (ECCV); 2018. p. 366-82.
39. Ma C, Yang C, Yang F, Zhuang Y, Zhang Z, Jia H, et al. Trajectory factory: Tracklet cleaving and re-connection by deep siamese bi-gru for multiple object tracking. In: 2018 IEEE International Conference on Multimedia and Expo (ICME). IEEE; 2018. p. 1-6.
40. Sadeghian A, Alahi A, Savarese S. Tracking the untrackable: Learning to track multiple cues with long-term dependencies. In: Proceedings of the IEEE International Conference on Computer Vision; 2017. p. 300-11.
41. Kim M, Alletto S, Rigazio L. Similarity mapping with enhanced siamese network for multi-object tracking. arXiv preprint arXiv:160909156. 2016.
42. Wang B, Wang L, Shuai B, Zuo Z, Liu T, Luk Chan K, et al. Joint learning of convolutional neural networks and temporally constrained metrics for tracklet association. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops; 2016. p. 1-8.
43. Leal-Taixé L, Canton-Ferrer C, Schindler K. Learning by tracking: Siamese CNN for robust target association. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops; 2016. p. 33-40.
44. Son J, Baek M, Cho M, Han B. Multi-object tracking with quadruplet convolutional neural networks. In: Proceedings of the IEEE conference on computer vision and pattern recognition; 2017. p. 5620-9.
45. Zhou Z, Xing J, Zhang M, Hu W. Online multi-target tracking with tensor-based high-order graph matching. In: 2018 24th International Conference on Pattern Recognition (ICPR). IEEE; 2018. p. 1809-14.
46. Wang Q, Zhang L, Bertinetto L, Hu W, Torr PH. Fast online object tracking and segmentation: A unifying approach. In: Proceedings of the IEEE conference on computer vision and pattern recognition; 2019. .
47. Li B, Wu W, Wang Q, Zhang F, Xing J, Yan J. Siamrpn++: Evolution of siamese visual tracking with very deep networks. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition; 2019. p. 4282-91.
48. Dinh H, Tang H. Development of a tracking-based system for automated traffic data collection for roundabouts. Journal of Modern Transportation. 2017;25(1):12-23.
49. Kaur H, Sahambi J. Vehicle tracking in video using fractional feedback Kalman filter. IEEE Transactions on Computational Imaging. 2016;2(4):550-61.
50. O’Malley R, Jones E, Glavin M. Rear-lamp vehicle detection and tracking in low-exposure color video for night conditions. IEEE Transactions on Intelligent Transportation Systems. 2010;11(2):453-62.
51. Teoh SS, Bräunl T. A reliability point and kalman filter-based vehicle tracking technique. In: International Conference on Intelligent Systems; 2012. p. 134-8.
52. Khalkhali MB, Vahedian A, Yazdi HS. Vehicle tracking with Kalman filter using online situation assessment. Robotics and Autonomous Systems. 2020;131:103596.
53. Chen Z, Ellis T, Velastin SA. Vehicle detection, tracking and classification in urban traffic. In: 2012 15th International IEEE Conference on Intelligent Transportation Systems. IEEE; 2012. p. 951-6.
54. Jazayeri A, Cai H, Zheng JY, Tuceryan M. Vehicle detection and tracking in car video based on motion model. IEEE Transactions on Intelligent Transportation Systems. 2011;12(2):583-95.
55. Luvizon DC, Nassu BT, Minetto R. A video-based system for vehicle speed measurement in urban roadways. IEEE Transactions on Intelligent Transportation Systems. 2016;18(6):1393-404.
56. Yang C, Wanyu L, Yanli Z, Hong L. The research of video tracking based on improved SIFT algorithm. In: 2016 IEEE International Conference on Mechatronics and Automation. IEEE; 2016. p. 1703-7.
57. Leal-Taixé L, Milan A, Reid I, Roth S, Schindler K. Motchallenge 2015: Towards a benchmark for multi-target tracking. arXiv preprint arXiv:150401942. 2015.
58. Scheidegger S, Benjaminsson J, Rosenberg E, Krishnan A, Granström K. Mono-camera 3d multi-object track- ing using deep learning detections and pmbm filtering. In: 2018 IEEE Intelligent Vehicles Symposium (IV). IEEE; 2018. p. 433-40.
59. Zou Y, Zhang W, Weng W, Meng Z. Multi-Vehicle Tracking via Real-Time Detection Probes and a Markov Decision Process Policy. Sensors. 2019;19(6):1309.
60. Fernández-Sanjurjo M, Bosquet B, Mucientes M, Brea VM. Real-time visual detection and tracking system for traffic monitoring. Engineering Applications of Artificial Intelligence. 2019;85:410-20.
61. Qiu H, Liu X, Rallapalli S, Bency AJ, Chan K, Urgaonkar R, et al. Kestrel: Video analytics for augmented multi-camera vehicle tracking. In: 2018 IEEE/ACM Third International Conference on Internet-of-Things Design and Implementation (IoTDI). IEEE; 2018. p. 48-59.
62. López-Sastre RJ, Herranz-Perdiguero C, Guerrero-Gómez-Olmedo R, Oñoro-Rubio D, Maldonado-Bascón

S. Boosting multi-vehicle tracking with a joint object detection and viewpoint estimation sensor. Sensors. 2019;19(19):4062.

1. García-Fernández ÁF, Williams JL, Granström K, Svensson L. Poisson multi-Bernoulli mixture filter: direct derivation and implementation. IEEE Transactions on Aerospace and Electronic Systems. 2018;54(4):1883- 901.
2. Li P, Li G, Yan Z, Li Y, Lu M, Xu P, et al. Spatio-temporal Consistency and Hierarchical Matching for Multi- Target Multi-Camera Vehicle Tracking. In: CVPR Workshops; 2019. p. 222-30.
3. Nikodem M, Słabicki M, Surmacz T, Mrówka P, Dołe˛ga C. Multi-Camera Vehicle Tracking Using Edge Com- puting and Low-Power Communication. Sensors. 2020;20(11):3334.
4. Zhao T, Li M, Chen G, Wang Y. Autonomous Vehicle Tracking Control Using Deep Learning and Stereo Vision. In: 2018 IEEE International Conference on Computational Intelligence and Virtual Environments for Measurement Systems and Applications (CIVEMSA). IEEE; 2018. p. 1-6.
5. Wang J, Simeonova S, Shahbazi M. Orientation-and Scale-Invariant Multi-Vehicle Detection and Tracking from Unmanned Aerial Videos. Remote Sensing. 2019;11(18):2155.
6. Usmankhujaev S, Baydadaev S, Woo KJ. Real-Time, Deep Learning Based Wrong Direction Detection. Ap- plied Sciences. 2020;10(7):2453.
7. Kwan C, Chou B, Echavarren A, Budavari B, Li J, Tran T. Compressive vehicle tracking using deep learning. In: 2018 9th IEEE Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON). IEEE; 2018. p. 51-6.
8. Kirillov A, He K, Girshick R, Rother C, Dollár P. Panoptic segmentation. In: Proceedings of the IEEE confer- ence on computer vision and pattern recognition; 2019. p. 9404-13.
9. Wei Y, Xiao H, Shi H, Jie Z, Feng J, Huang TS. Revisiting dilated convolution: A simple approach for weakly- and semi-supervised semantic segmentation. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition; 2018. p. 7268-77.
10. Hong S, Noh H, Han B. Decoupled deep neural network for semi-supervised semantic segmentation. Advances in neural information processing systems. 2015;28:1495-503.
11. Souly N, Spampinato C, Shah M. Semi supervised semantic segmentation using generative adversarial network. In: Proceedings of the IEEE International Conference on Computer Vision; 2017. p. 5688-96.
12. Hung WC, Tsai YH, Liou YT, Lin YY, Yang MH. Adversarial learning for semi-supervised semantic segmen- tation. arXiv preprint arXiv:180207934. 2018.
13. Long J, Shelhamer E, Darrell T. Fully convolutional networks for semantic segmentation. In: Proceedings of the IEEE conference on computer vision and pattern recognition; 2015. p. 3431-40.
14. Ronneberger O, Fischer P, Brox T. U-Net: Convolutional Networks for Biomedical Image Segmentation. CoRR. 2015;abs/1505.04597. Available from: <http://arxiv.org/abs/1505.04597>.
15. Badrinarayanan V, Kendall A, Cipolla R. Segnet: A deep convolutional encoder-decoder architecture for image segmentation. IEEE transactions on pattern analysis and machine intelligence. 2017;39(12):2481-95.
16. Cheng B, Chen LC, Wei Y, Zhu Y, Huang Z, Xiong J, et al. Spgnet: Semantic prediction guidance for scene parsing. In: Proceedings of the IEEE/CVF International Conference on Computer Vision; 2019. p. 5218-28.
17. Yu F, Koltun V. Multi-scale context aggregation by dilated convolutions. arXiv preprint arXiv:151107122. 2015.
18. Chen LC, Papandreou G, Kokkinos I, Murphy K, Yuille AL. Deeplab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected crfs. IEEE transactions on pattern analysis and machine intelligence. 2017;40(4):834-48.
19. Paszke A, Chaurasia A, Kim S, Culurciello E. Enet: A deep neural network architecture for real-time semantic segmentation. arXiv preprint arXiv:160602147. 2016.
20. Chen LC, Papandreou G, Schroff F, Adam H. Rethinking atrous convolution for semantic image segmentation. arXiv preprint arXiv:170605587. 2017.
21. Peng C, Zhang X, Yu G, Luo G, Sun J. Large kernel matters–improve semantic segmentation by global convo- lutional network. In: Proceedings of the IEEE conference on computer vision and pattern recognition; 2017. p. 4353-61.
22. Liu W, Rabinovich A, Berg AC. Parsenet: Looking wider to see better. arXiv preprint arXiv:150604579. 2015.
23. Pinheiro PO, Lin TY, Collobert R, Dollár P. Learning to refine object segments. In: European conference on computer vision. Springer; 2016. p. 75-91.
24. Lin G, Milan A, Shen C, Reid I. Refinenet: Multi-path refinement networks for high-resolution semantic segmentation. In: Proceedings of the IEEE conference on computer vision and pattern recognition; 2017. p. 1925-34.
25. Visin F, Ciccone M, Romero A, Kastner K, Cho K, Bengio Y, et al. Reseg: A recurrent neural network-based model for semantic segmentation. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops; 2016. p. 41-8.
26. Li Z, Gan Y, Liang X, Yu Y, Cheng H, Lin L. Lstm-cf: Unifying context modeling and fusion with lstms for rgb-d scene labeling. In: European conference on computer vision. Springer; 2016. p. 541-57.
27. Zhang L, Li X, Arnab A, Yang K, Tong Y, Torr PH. Dual graph convolutional network for semantic segmenta- tion. arXiv preprint arXiv:190906121. 2019.
28. Zhao H, Shi J, Qi X, Wang X, Jia J. Pyramid scene parsing network. In: Proceedings of the IEEE conference on computer vision and pattern recognition; 2017. p. 2881-90.
29. Yuan Y, Chen X, Wang J. Object-contextual representations for semantic segmentation. In: Computer Vision– ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part VI 16. Springer; 2020. p. 173-90.
30. Qi CR, Su H, Mo K, Guibas LJ. Pointnet: Deep learning on point sets for 3d classification and segmentation. In: Proceedings of the IEEE conference on computer vision and pattern recognition; 2017. p. 652-60.
31. Qi CR, Yi L, Su H, Guibas LJ. Pointnet++: Deep hierarchical feature learning on point sets in a metric space. In: Advances in neural information processing systems; 2017. p. 5099-108.
32. Huang J, You S. Point cloud labeling using 3d convolutional neural network. In: 2016 23rd International Conference on Pattern Recognition (ICPR). IEEE; 2016. p. 2670-5.
33. Romera E, Alvarez JM, Bergasa LM, Arroyo R. Erfnet: Efficient residual factorized convnet for real-time semantic segmentation. IEEE Transactions on Intelligent Transportation Systems. 2017;19(1):263-72.
34. Lyu H, Fu H, Hu X, Liu L. ESNet: Edge-based segmentation network for real-time semantic segmentation in traffic scenes. In: 2019 IEEE International Conference on Image Processing (ICIP). IEEE; 2019. p. 1855-9.
35. Deng L, Yang M, Qian Y, Wang C, Wang B. CNN based semantic segmentation for urban traffic scenes using fisheye camera. In: 2017 IEEE Intelligent Vehicles Symposium (IV). IEEE; 2017. p. 231-6.
36. Sáez A, Bergasa LM, Romeral E, López E, Barea R, Sanz R. CNN-based fisheye image real-time semantic segmentation. In: 2018 IEEE Intelligent Vehicles Symposium (IV). IEEE; 2018. p. 1039-44.
37. Kendall A, Badrinarayanan V, Cipolla R. Bayesian segnet: Model uncertainty in deep convolutional encoder- decoder architectures for scene understanding. arXiv preprint arXiv:151102680. 2015.
38. Ohgushi T, Horiguchi K, Yamanaka M. Road Obstacle Detection Method Based on an Autoencoder with Semantic Segmentation. In: Proceedings of the Asian Conference on Computer Vision; 2020. .
39. Hua M, Nan Y, Lian S. Small Obstacle Avoidance Based on RGB-D Semantic Segmentation. In: Proceedings of the IEEE International Conference on Computer Vision Workshops; 2019. p. 0-0.
40. Levi D, Garnett N, Fetaya E, Herzlyia I. StixelNet: A Deep Convolutional Network for Obstacle Detection and Road Segmentation. In: BMVC. vol. 1; 2015. p. 4.
41. Deepika N, Variyar VS. Obstacle classification and detection for vision based navigation for autonomous driving. In: 2017 International Conference on Advances in Computing, Communications and Informatics (ICACCI). IEEE; 2017. p. 2092-7.
42. Schneider L, Cordts M, Rehfeld T, Pfeiffer D, Enzweiler M, Franke U, et al. Semantic stixels: Depth is not enough. In: 2016 IEEE Intelligent Vehicles Symposium (IV). IEEE; 2016. p. 110-7.
43. Cordts M, Rehfeld T, Schneider L, Pfeiffer D, Enzweiler M, Roth S, et al. The stixel world: A medium-level representation of traffic scenes. Image and Vision Computing. 2017;68:40-52.
44. Hariharan B, Arbeláez P, Girshick R, Malik J. Simultaneous detection and segmentation. In: European Confer- ence on Computer Vision. Springer; 2014. p. 297-312.
45. Dai J, He K, Sun J. Instance-aware semantic segmentation via multi-task network cascades. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition; 2016. p. 3150-8.
46. Pinheiro PO, Collobert R, Dollár P. Learning to segment object candidates. In: Advances in Neural Information Processing Systems; 2015. p. 1990-8.
47. Dai J, He K, Li Y, Ren S, Sun J. Instance-sensitive fully convolutional networks. In: European Conference on Computer Vision. Springer; 2016. p. 534-49.
48. Li Y, Qi H, Dai J, Ji X, Wei Y. Fully convolutional instance-aware semantic segmentation. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition; 2017. p. 2359-67.
49. Bolya D, Zhou C, Xiao F, Lee YJ. Yolact: Real-time instance segmentation. In: Proceedings of the IEEE international conference on computer vision; 2019. p. 9157-66.
50. Bolya D, Zhou C, Xiao F, Lee YJ. Yolact++: Better real-time instance segmentation. arXiv preprint arXiv:191206218. 2019.
51. Wang X, Kong T, Shen C, Jiang Y, Li L. Solo: Segmenting objects by locations. arXiv preprint arXiv:191204488. 2019.
52. Wang X, Zhang R, Kong T, Li L, Shen C. SOLOv2: Dynamic, Faster and Stronger. arXiv preprint arXiv:200310152. 2020.
53. Chen H, Sun K, Tian Z, Shen C, Huang Y, Yan Y. BlendMask: Top-down meets bottom-up for instance segmentation. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition; 2020. p. 8573-81.
54. Lee Y, Park J. CenterMask: Real-time anchor-free instance segmentation. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition; 2020. p. 13906-15.
55. Xie E, Sun P, Song X, Wang W, Liu X, Liang D, et al. Polarmask: Single shot instance segmentation with polar representation. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition; 2020. p. 12193-202.
56. Zhang Z, Schwing AG, Fidler S, Urtasun R. Monocular object instance segmentation and depth ordering with cnns. In: Proceedings of the IEEE International Conference on Computer Vision; 2015. p. 2614-22.
57. Mou L, Zhu XX. Vehicle instance segmentation from aerial image and video using a multitask learning residual fully convolutional network. IEEE Transactions on Geoscience and Remote Sensing. 2018;56(11):6699-711.
58. Zhang B, Zhang J. A Traffic Surveillance System for Obtaining Comprehensive Information of the Passing Vehicles Based on Instance Segmentation. IEEE Transactions on Intelligent Transportation Systems. 2020.
59. Huang L, Chen Y, Fan Z, Chen Z. Measuring the absolute distance of a front vehicle from an in-car camera based on monocular vision and instance segmentation. Journal of Electronic Imaging. 2018;27(4):043019.
60. Neven D, De Brabandere B, Georgoulis S, Proesmans M, Van Gool L. Towards end-to-end lane detection: an instance segmentation approach. In: 2018 IEEE intelligent vehicles symposium (IV). IEEE; 2018. p. 286-91.
61. Roberts B, Kaltwang S, Samangooei S, Pender-Bare M, Tertikas K, Redford J. A Dataset for Lane Instance Seg- mentation in Urban Environments. In: Proceedings of the European Conference on Computer Vision (ECCV); 2018. p. 533-49.
62. Hadi S, Phon-Amnuaisuk S, Tan SJ. Semantic Instance Segmentation in a 3D Traffic Scene Reconstruction task. In: 2020 59th Annual Conference of the Society of Instrument and Control Engineers of Japan (SICE). IEEE; 2020. p. 186-91.
63. Varma G, Subramanian A, Namboodiri A, Chandraker M, Jawahar C. IDD: A dataset for exploring problems of autonomous navigation in unconstrained environments. In: 2019 IEEE Winter Conference on Applications of Computer Vision (WACV). IEEE; 2019. p. 1743-51.
64. Zendel O, Honauer K, Murschitz M, Steininger D, Fernandez Dominguez G. Wilddash-creating hazard-aware benchmarks. In: Proceedings of the European Conference on Computer Vision (ECCV); 2018. p. 402-16.
65. Lowe DG. Distinctive image features from scale-invariant keypoints. International journal of computer vision. 2004;60(2):91-110.
66. Ojala T, Pietikainen M, Maenpaa T. Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. IEEE Transactions on pattern analysis and machine intelligence. 2002;24(7):971-87.
67. Tang K, Yao B, Fei-Fei L, Koller D. Combining the right features for complex event recognition. In: Proceed- ings of the IEEE International Conference on Computer Vision; 2013. p. 2696-703.
68. Leutenegger S, Chli M, Siegwart RY. BRISK: Binary robust invariant scalable keypoints. In: 2011 International conference on computer vision. Ieee; 2011. p. 2548-55.
69. Rosten E, Drummond T. Machine learning for high-speed corner detection. In: European conference on computer vision. Springer; 2006. p. 430-43.
70. Viswanathan DG. Features from accelerated segment test (fast). In: Proceedings of the 10th workshop on Image Analysis for Multimedia Interactive Services, London, UK; 2009. p. 6-8.
71. Friedman A. Framing pictures: The role of knowledge in automatized encoding and memory for gist. Journal of experimental psychology: General. 1979;108(3):316.
72. Oliva A, Torralba A. Modeling the shape of the scene: A holistic representation of the spatial envelope. Inter- national journal of computer vision. 2001;42(3):145-75.
73. Chen My, Hauptmann A. Mosift: Recognizing human actions in surveillance videos. 2009.
74. Laptev I. On space-time interest points. International journal of computer vision. 2005;64(2-3):107-23.
75. Wang H, Kläser A, Schmid C, Liu CL. Action recognition by dense trajectories. In: CVPR 2011. IEEE; 2011. p. 3169-76.
76. Wang H, Schmid C. Action recognition with improved trajectories. In: Proceedings of the IEEE international conference on computer vision; 2013. p. 3551-8.
77. Hasan M, Choi J, Neumann J, Roy-Chowdhury AK, Davis LS. Learning temporal regularity in video sequences. In: Proceedings of the IEEE conference on computer vision and pattern recognition; 2016. p. 733-42.
78. Feng Y, Yuan Y, Lu X. Deep representation for abnormal event detection in crowded scenes. In: Proceedings of the 24th ACM international conference on Multimedia; 2016. p. 591-5.
79. Jiang H, Lu Y, Xue J. Automatic soccer video event detection based on a deep neural network combined cnn and rnn. In: 2016 IEEE 28th International Conference on Tools with Artificial Intelligence (ICTAI). IEEE; 2016. p. 490-4.
80. Wang L, Zhou F, Li Z, Zuo W, Tan H. Abnormal event detection in videos using hybrid spatio-temporal autoencoder. In: 2018 25th IEEE International Conference on Image Processing (ICIP). IEEE; 2018. p. 2276- 80.
81. Chong YS, Tay YH. Abnormal event detection in videos using spatiotemporal autoencoder. In: International Symposium on Neural Networks. Springer; 2017. p. 189-96.
82. Medel JR, Savakis A. Anomaly detection in video using predictive convolutional long short-term memory networks. arXiv preprint arXiv:161200390. 2016.
83. Liu AA, Shao Z, Wong Y, Li J, Su YT, Kankanhalli M. LSTM-based multi-label video event detection. Multi- media Tools and Applications. 2019;78(1):677-95.
84. Feng Q, Gao C, Wang L, Zhao Y, Song T, Li Q. Spatio-temporal fall event detection in complex scenes using attention guided LSTM. Pattern Recognition Letters. 2020;130:242-9.
85. Giannakeris P, Kaltsa V, Avgerinakis K, Briassouli A, Vrochidis S, Kompatsiaris I. Speed estimation and abnormality detection from surveillance cameras. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops; 2018. p. 93-9.
86. Zhou S, Shen W, Zeng D, Fang M, Wei Y, Zhang Z. Spatial–temporal convolutional neural networks for anomaly detection and localization in crowded scenes. Signal Processing: Image Communication. 2016;47:358- 68.
87. Franklin RJ, et al. Traffic Signal Violation Detection using Artificial Intelligence and Deep Learning. In: 2020 5th International Conference on Communication and Electronics Systems (ICCES). IEEE; 2020. p. 839-44.
88. Xu D, Ricci E, Yan Y, Song J, Sebe N. Learning deep representations of appearance and motion for anomalous event detection. arXiv preprint arXiv:151001553. 2015.
89. Xu D, Yan Y, Ricci E, Sebe N. Detecting anomalous events in videos by learning deep representations of appearance and motion. Computer Vision and Image Understanding. 2017;156:117-27.
90. Anno S, Sasaki Y. GAN-based Abnormal Detection by Recognizing Ungeneratable Patterns. In: Asian Con- ference on Pattern Recognition. Springer; 2019. p. 401-11.
91. Ravanbakhsh M, Sangineto E, Nabi M, Sebe N. Training adversarial discriminators for cross-channel abnormal event detection in crowds. In: 2019 IEEE Winter Conference on Applications of Computer Vision (WACV). IEEE; 2019. p. 1896-904.
92. Nguyen KT, Dinh DT, Do MN, Tran MT. Anomaly Detection in Traffic Surveillance Videos with GAN-based Future Frame Prediction. In: Proceedings of the 2020 International Conference on Multimedia Retrieval; 2020. p. 457-63.
93. Aköz Ö, Karsligil ME. Traffic event classification at intersections based on the severity of abnormality. Machine vision and applications. 2014;25(3):613-32.
94. Kaviani R, Ahmadi P, Gholampour I. Automatic accident detection using topic models. In: 2015 23rd Iranian Conference on Electrical Engineering. IEEE; 2015. p. 444-9.
95. Fu DY, Crichton W, Hong J, Yao X, Zhang H, Truong A, et al. Rekall: Specifying video events using composi- tions of spatiotemporal labels. arXiv preprint arXiv:191002993. 2019.
96. Yao Y, Xu M, Wang Y, Crandall DJ, Atkins EM. Unsupervised traffic accident detection in first-person videos. arXiv preprint arXiv:190300618. 2019.
97. Tian D, Zhang C, Duan X, Wang X. An automatic car accident detection method based on cooperative vehicle infrastructure systems. IEEE Access. 2019;7:127453-63.
98. Kim H, Park S, Paik J. Pre-Activated 3D CNN and Feature Pyramid Network for Traffic Accident Detection. In: 2020 IEEE International Conference on Consumer Electronics (ICCE). IEEE; 2020. p. 1-3.
99. Ijjina EP, Chand D, Gupta S, Goutham K. Computer Vision-based Accident Detection in Traffic Surveillance. In: 2019 10th International Conference on Computing, Communication and Networking Technologies (ICC- CNT). IEEE; 2019. p. 1-6.
100. Shah AP, Lamare JB, Nguyen-Anh T, Hauptmann A. Cadp: A novel dataset for cctv traffic camera based acci- dent analysis. In: 2018 15th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS). IEEE; 2018. p. 1-9.
101. Chan FH, Chen YT, Xiang Y, Sun M. Anticipating accidents in dashcam videos. In: Asian Conference on Computer Vision. Springer; 2016. p. 136-53.
102. Srinivasan A, Srikanth A, Indrajit H, Narasimhan V. A Novel Approach for Road Accident Detection using DETR Algorithm. In: 2020 International Conference on Intelligent Data Science Technologies and Applications (IDSTA). IEEE; 2020. p. 75-80.
103. Carion N, Massa F, Synnaeve G, Usunier N, Kirillov A, Zagoruyko S. End-to-End Object Detection with Transformers. arXiv preprint arXiv:200512872. 2020.
104. Suzuki T, Kataoka H, Aoki Y, Satoh Y. Anticipating traffic accidents with adaptive loss and large-scale incident db. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition; 2018. p. 3521-9.
105. Donahue J, Jia Y, Vinyals O, Hoffman J, Zhang N, Tzeng E, et al. Decaf: A deep convolutional activation feature for generic visual recognition. In: International conference on machine learning; 2014. p. 647-55.
106. Arceda VEM, Riveros EL. Fast car crash detection in video. In: 2018 XLIV Latin American Computer Conference (CLEI). IEEE; 2018. p. 632-7.
107. Hassner T, Itcher Y, Kliper-Gross O. Violent flows: Real-time detection of violent crowd behavior. In: 2012 IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops. IEEE; 2012. p. 1-6.
108. Biradar KM, Gupta A, Mandal M, Vipparthi SK. Challenges in time-stamp aware anomaly detection in traffic videos. arXiv preprint arXiv:190604574. 2019.
109. Xu Y, Ouyang X, Cheng Y, Yu S, Xiong L, Ng CC, et al. Dual-mode vehicle motion pattern learning for high performance road traffic anomaly detection. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops; 2018. p. 145-52.
110. Doshi K, Yilmaz Y. Fast unsupervised anomaly detection in traffic videos. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops; 2020. p. 624-5.
111. St-Aubin P, Saunier N, Miranda-Moreno L. Large-scale automated proactive road safety analysis using video data. Transportation Research Part C: Emerging Technologies. 2015;58:363-79.
112. Saunier N, Sayed T. A feature-based tracking algorithm for vehicles in intersections. In: The 3rd Canadian Conference on Computer and Robot Vision (CRV’06). IEEE; 2006. p. 59-9.
113. Fu T, Hu W, Miranda-Moreno L, Saunier N. Investigating secondary pedestrian-vehicle interactions at non- signalized intersections using vision-based trajectory data. Transportation research part C: emerging technolo- gies. 2019;105:222-40.
114. Noh B, Park H, Yeo H. Analyzing vehicle–pedestrian interactions: Combining data cube structure and predictive collision risk estimation model. Accident Analysis & Prevention. 2022;165:106539.
115. Chen X, Wang H, Razi A, Russo B, Pacheco J, Roberts J, et al. Network-level Safety Metrics for Overall Traffic Safety Assessment: A Case Study. arXiv preprint arXiv:220113229. 2022.
116. Zangenehpour S, Strauss J, Miranda-Moreno LF, Saunier N. Are signalized intersections with cycle tracks safer? A case–control study based on automated surrogate safety analysis using video data. Accident Analysis & Prevention. 2016;86:161-72.
117. Zangenehpour S, Miranda-Moreno LF, Saunier N. Automated classification based on video data at intersec- tions with heavy pedestrian and bicycle traffic: Methodology and application. Transportation research part C: emerging technologies. 2015;56:161-76.
118. Lu Z, Fu T, Fu L, Shiravi S, Jiang C. A video-based approach to calibrating car-following parameters in VISSIM for urban traffic. International journal of transportation science and technology. 2016;5(1):1-9.
119. Mohamed MG, Saunier N. The impact of motion prediction methods on surrogate safety analysis: A case study of left-turn and opposite-direction interactions at a signalized intersection in Montreal. Journal of Transportation Safety & Security. 2018;10(4):265-87.
120. Xu W, Ruiz-Juri N, Huang R, Duthie J, Clary J. Automated pedestrian safety analysis using data from traffic monitoring cameras. In: Proceedings of the 1st ACM/EIGSCC Symposium on Smart Cities and Communities; 2018. p. 1-8.
121. Battiato S, Farinella GM, Gallo G, Giudice O. On-board monitoring system for road traffic safety analysis. Computers in Industry. 2018;98:208-17.
122. Comaniciu D, Ramesh V, Meer P. Kernel-based object tracking. IEEE Transactions on pattern analysis and machine intelligence. 2003;25(5):564-77.
123. TRAFXSAFE - Automated Road Safety Analysis; 2022. Available from: [https://safety.transoftsolut](https://safety.transoftsolutions.com/trafxsafe/) [ions.com/trafxsafe/](https://safety.transoftsolutions.com/trafxsafe/).
124. Xie K, Ozbay K, Yang H, Li C. Mining automatically extracted vehicle trajectory data for proactive safety analytics. Transportation research part C: emerging technologies. 2019;106:61-72.
125. Chen AY, Chiu YL, Hsieh MH, Lin PW, Angah O. Conflict analytics through the vehicle safety space in mixed traffic flows using UAV image sequences. Transportation research part C: emerging technologies. 2020;119:102744.
126. Yang D, Ozbay K, Xie K, Yang H, Zuo F, Sha D. Proactive safety monitoring: A functional approach to detect safety-related anomalies using unmanned aerial vehicle video data. Transportation research part C: emerging technologies. 2021;127:103130.
127. Simonovsky M, Komodakis N. Dynamic edge-conditioned filters in convolutional neural networks on graphs. In: Proceedings of the IEEE conference on computer vision and pattern recognition; 2017. p. 3693-702.
128. Wu B, Wan A, Yue X, Keutzer K. Squeezeseg: Convolutional neural nets with recurrent crf for real-time road-object segmentation from 3d lidar point cloud. In: 2018 IEEE International Conference on Robotics and Automation (ICRA). IEEE; 2018. p. 1887-93.
129. Wu B, Zhou X, Zhao S, Yue X, Keutzer K. Squeezesegv2: Improved model structure and unsupervised domain adaptation for road-object segmentation from a lidar point cloud. In: 2019 International Conference on Robotics and Automation (ICRA). IEEE; 2019. p. 4376-82.
130. Milioto A, Vizzo I, Behley J, Stachniss C. Rangenet++: Fast and accurate lidar semantic segmentation. In: 2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). IEEE; 2019. p. 4213-20.
131. Xiang B, Tu J, Yao J, Li L. A novel octree-based 3-D fully convolutional neural network for point cloud classification in road environment. IEEE Transactions on Geoscience and Remote Sensing. 2019;57(10):7799- 818.
132. Nellore K, Hancke GP. A survey on urban traffic management system using wireless sensor networks. Sensors. 2016;16(2):157.
133. Bernas M, Płaczek B, Korski W, Loska P, Smyła J, Szymała P. A survey and comparison of low-cost sensing technologies for road traffic monitoring. Sensors. 2018;18(10):3243.
134. Won M. Intelligent traffic monitoring systems for vehicle classification: A survey. IEEE Access. 2020;8:73340- 58.
135. Ahangar MN, Ahmed QZ, Khan FA, Hafeez M. A survey of autonomous vehicles: enabling communication technologies and challenges. Sensors. 2021;21(3):706.
136. Farahani RZ, Miandoabchi E, Szeto WY, Rashidi H. A review of urban transportation network design problems. European Journal of Operational Research. 2013;229(2):281-302.
137. Yang H, H Bell MG. Models and algorithms for road network design: a review and some new developments. Transport Reviews. 1998;18(3):257-78.
138. Szeto W, Jiang Y, Wang D, Sumalee A. A sustainable road network design problem with land use transportation interaction over time. Networks and Spatial Economics. 2015;15(3):791-822.
139. Hosseininasab SM, Shetab-Boushehri SN. Integration of selecting and scheduling urban road construction projects as a time-dependent discrete network design problem. European Journal of Operational Research. 2015;246(3):762-71.
140. Fan W, Machemehl RB. Optimal transit route network design problem with variable transit demand: genetic algorithm approach. Journal of transportation engineering. 2006;132(1):40-51.
141. Yan Y, Liu Z, Meng Q, Jiang Y. Robust optimization model of bus transit network design with stochastic travel time. Journal of Transportation Engineering. 2013;139(6):625-34.
142. Cancela H, Mauttone A, Urquhart ME. Mathematical programming formulations for transit network design. Transportation Research Part B: Methodological. 2015;77:17-37.
143. Liu J, Zhou X. Capacitated transit service network design with boundedly rational agents. Transportation Research Part B: Methodological. 2016;93:225-50.
144. Di Z, Yang L, Qi J, Gao Z. Transportation network design for maximizing flow-based accessibility. Transporta- tion Research Part B: Methodological. 2018;110:209-38.
145. Guo J, Huang W, Williams BM. Adaptive Kalman filter approach for stochastic short-term traffic flow rate prediction and uncertainty quantification. Transportation Research Part C: Emerging Technologies. 2014;43:50- 64.
146. Qi Y, Ishak S. A Hidden Markov Model for short term prediction of traffic conditions on freeways. Transporta- tion Research Part C: Emerging Technologies. 2014;43:95-111.
147. Wang J, Deng W, Guo Y. New Bayesian combination method for short-term traffic flow forecasting. Trans- portation Research Part C: Emerging Technologies. 2014;43:79-94.
148. Ma X, Tao Z, Wang Y, Yu H, Wang Y. Long short-term memory neural network for traffic speed prediction using remote microwave sensor data. Transportation Research Part C: Emerging Technologies. 2015;54:187-97.
149. Cui Z, Ke R, Pu Z, Wang Y. Deep bidirectional and unidirectional LSTM recurrent neural network for network- wide traffic speed prediction. arXiv preprint arXiv:180102143. 2018.
150. Du S, Li T, Gong X, Horng SJ. A hybrid method for traffic flow forecasting using multimodal deep learning. arXiv preprint arXiv:180302099. 2018.
151. Wang J, Chen R, He Z. Traffic speed prediction for urban transportation network: A path based deep learning approach. Transportation Research Part C: Emerging Technologies. 2019;100:372-85.
152. Mannering F, Bhat CR, Shankar V, Abdel-Aty M. Big data, traditional data and the tradeoffs between prediction and causality in highway-safety analysis. Analytic methods in accident research. 2020;25:100113.
153. Part D. Highway safety manual. Aashto; 2010.
154. Bhat CR, Born K, Sidharthan R, Bhat PC. A count data model with endogenous covariates: formulation and application to roadway crash frequency at intersections. Analytic Methods in Accident Research. 2014;1:53-71.
155. Mannering FL, Shankar V, Bhat CR. Unobserved heterogeneity and the statistical analysis of highway accident data. Analytic methods in accident research. 2016;11:1-16.
156. Arbabzadeh N, Jafari M. A data-driven approach for driving safety risk prediction using driver behavior and roadway information data. IEEE transactions on intelligent transportation systems. 2017;19(2):446-60.
157. Cheng N, Lyu F, Chen J, Xu W, Zhou H, Zhang S, et al. Big data driven vehicular networks. IEEE Network. 2018;32(6):160-7.
158. Lord D, Geedipally SR, Guikema SD. Extension of the application of Conway-Maxwell-Poisson models: Ana- lyzing traffic crash data exhibiting underdispersion. Risk Analysis: An International Journal. 2010;30(8):1268- 76.
159. Aguero-Valverde J, Jovanis PP. Analysis of road crash frequency with spatial models. Transportation Research Record. 2008;2061(1):55-63.
160. Karlaftis MG, Golias I. Effects of road geometry and traffic volumes on rural roadway accident rates. Accident Analysis & Prevention. 2002;34(3):357-65.
161. Othman S, Thomson R, Lannér G. Identifying critical road geometry parameters affecting crash rate and crash type. In: Annals of Advances in Automotive Medicine/Annual Scientific Conference. vol. 53. Association for the Advancement of Automotive Medicine; 2009. p. 155.
162. Yu R, Abdel-Aty M. Multi-level Bayesian analyses for single-and multi-vehicle freeway crashes. Accident Analysis & Prevention. 2013;58:97-105.
163. Ahmed M, Abdel-Aty M. A data fusion framework for real-time risk assessment on freeways. Transportation Research Part C: Emerging Technologies. 2013;26:203-13.
164. Xu C, Wang W, Liu P, Guo R, Li Z. Using the Bayesian updating approach to improve the spatial and temporal transferability of real-time crash risk prediction models. Transportation research part C: emerging technologies. 2014;38:167-76.
165. Yu R, Wang Y, Zou Z, Wang L. Convolutional neural networks with refined loss functions for the real-time crash risk analysis. Transportation research part C: emerging technologies. 2020;119:102740.
166. Sun J, Sun J. A dynamic Bayesian network model for real-time crash prediction using traffic speed conditions data. Transportation Research Part C: Emerging Technologies. 2015;54:176-86.
167. Sameen MI, Pradhan B. Severity prediction of traffic accidents with recurrent neural networks. Applied Sci- ences. 2017;7(6):476.
168. Al-Sarawi S, Anbar M, Alieyan K, Alzubaidi M. Internet of Things (IoT) communication protocols. In: 2017 8th International conference on information technology (ICIT). IEEE; 2017. p. 685-90.
169. Allal S, Boudjit S. Geocast routing protocols for vanets: Survey and guidelines. In: 2012 Sixth International Conference on Innovative Mobile and Internet Services in Ubiquitous Computing. IEEE; 2012. p. 323-8.
170. Boussoufa-Lahlah S, Semchedine F, Bouallouche-Medjkoune L. Geographic routing protocols for Vehicular Ad hoc NETworks (VANETs): A survey. Vehicular Communications. 2018;11:20-31.
171. Dhankhar S, Agrawal S. VANETs: A survey on routing protocols and issues. International Journal of Innovative Research in Science, Engineering and Technology. 2014;3(6):13427-35.
172. Allal S, Boudjit S. Geocast Routing Protocols for VANETs: Survey and Geometry-Driven Scheme Proposal. J Internet Serv Inf Secur. 2013;3(1/2):20-36.
173. Martinez FJ, Toh CK, Cano JC, Calafate CT, Manzoni P. A survey and comparative study of simulators for vehicular ad hoc networks (VANETs). Wireless Communications and Mobile Computing. 2011;11(7):813-28.
174. Luo J, Hubaux JP. A survey of inter-vehicle communication; 2004.
175. Chen Z, Wu C, Huang Z, Lyu N, Hu Z, Zhong M, et al. Dangerous driving behavior detection using video- extracted vehicle trajectory histograms. Journal of Intelligent Transportation Systems. 2017;21(5):409-21.
176. Ramyar S, Homaifar A, Karimoddini A, Tunstel E. Identification of anomalies in lane change behavior using one-class SVM. In: 2016 IEEE International Conference on Systems, Man, and Cybernetics (SMC). IEEE; 2016. p. 004405-10.
177. Kaltsa V, Briassouli A, Kompatsiaris I, Strintzis MG. Multiple Hierarchical Dirichlet Processes for anomaly detection in traffic. Computer Vision and Image Understanding. 2018;169:28-39.
178. Wang J, Xia L, Hu X, Xiao Y. Abnormal event detection with semi-supervised sparse topic model. Neural Computing and Applications. 2019;31(5):1607-17.
179. Jiang E, et al. Analysis of abnormal vehicle behavior based on trajectory fitting. Journal of Computer and Communications. 2015;3(11):13.
180. Wonghabut P, Kumphong J, Ung-arunyawee R, Leelapatra W, Satiennam T. Traffic light color identification for automatic traffic light violation detection system. In: 2018 International Conference on Engineering, Applied Sciences, and Technology (ICEAST). IEEE; 2018. p. 1-4.
181. Dai Z, Song H, Wang X, Fang Y, Yun X, Zhang Z, et al. Video-based vehicle counting framework. IEEE Access. 2019;7:64460-70.
182. Nowosielski A, Frejlichowski D, Forczman´ski P, Gos´ciewska K, Hofman R. Automatic analysis of vehicle trajectory applied to visual surveillance. In: Image Processing and Communications Challenges 7. Springer; 2016. p. 89-96.
183. Datondji SRE, Dupuis Y, Subirats P, Vasseur P. A survey of vision-based traffic monitoring of road intersections. IEEE transactions on intelligent transportation systems. 2016;17(10):2681-98.
184. LeCun Y, Boser B, Denker JS, Henderson D, Howard RE, Hubbard W, et al. Backpropagation applied to handwritten zip code recognition. Neural computation. 1989;1(4):541-51.
185. Cho K, Van Merriënboer B, Bahdanau D, Bengio Y. On the properties of neural machine translation: Encoder- decoder approaches. arXiv preprint arXiv:14091259. 2014.
186. Hochreiter S, Schmidhuber J. Long short-term memory. Neural computation. 1997;9(8):1735-80.
187. Vaswani A, Shazeer N, Parmar N, Uszkoreit J, Jones L, Gomez AN, et al. Attention is all you need. Advances in neural information processing systems. 2017;30.
188. Han K, Wang Y, Chen H, Chen X, Guo J, Liu Z, et al. A survey on vision transformer. IEEE transactions on pattern analysis and machine intelligence. 2022.
189. Devlin J, Chang MW, Lee K, Toutanova K. Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:181004805. 2018.
190. Dosovitskiy A, Beyer L, Kolesnikov A, Weissenborn D, Zhai X, Unterthiner T, et al. An image is worth 16x16 words: Transformers for image recognition at scale. arXiv preprint arXiv:201011929. 2020.
191. Yuan L, Chen Y, Wang T, Yu W, Shi Y, Jiang ZH, et al. Tokens-to-token vit: Training vision transformers from scratch on imagenet. In: Proceedings of the IEEE/CVF International Conference on Computer Vision; 2021. p. 558-67.
192. McMahan B, Moore E, Ramage D, Hampson S, y Arcas BA. Communication-efficient learning of deep net- works from decentralized data. In: Artificial intelligence and statistics. PMLR; 2017. p. 1273-82.
193. Zhang C, Xie Y, Bai H, Yu B, Li W, Gao Y. A survey on federated learning. Knowledge-Based Systems. 2021;216:106775.
194. Li X, Huang K, Yang W, Wang S, Zhang Z. On the convergence of fedavg on non-iid data. arXiv preprint arXiv:190702189. 2019.
195. Liu Y, James J, Kang J, Niyato D, Zhang S. Privacy-preserving traffic flow prediction: A federated learning approach. IEEE Internet of Things Journal. 2020;7(8):7751-63.
196. Elbir AM, Soner B, Coleri S. Federated learning in vehicular networks. arXiv preprint arXiv:200601412. 2020.
197. Samarakoon S, Bennis M, Saad W, Debbah M. Federated learning for ultra-reliable low-latency V2V commu- nications. In: 2018 IEEE Global Communications Conference (GLOBECOM). IEEE; 2018. p. 1-7.
198. Zhang X, Peng M, Yan S, Sun Y. Deep-reinforcement-learning-based mode selection and resource allocation for cellular V2X communications. IEEE Internet of Things Journal. 2019;7(7):6380-91.
199. Nguyen DC, Ding M, Pathirana PN, Seneviratne A, Li J, Poor HV. Federated learning for internet of things: A comprehensive survey. IEEE Communications Surveys & Tutorials. 2021;23(3):1622-58.
200. Bagdasaryan E, Veit A, Hua Y, Estrin D, Shmatikov V. How to backdoor federated learning. In: International Conference on Artificial Intelligence and Statistics. PMLR; 2020. p. 2938-48.
201. Szegedy C, Zaremba W, Sutskever I, Bruna J, Erhan D, Goodfellow I, et al. Intriguing properties of neural networks. arXiv preprint arXiv:13126199. 2013.
202. Goodfellow IJ, Shlens J, Szegedy C. Explaining and harnessing adversarial examples. arXiv preprint arXiv:14126572. 2014.
203. Madry A, Makelov A, Schmidt L, Tsipras D, Vladu A. Towards deep learning models resistant to adversarial attacks. arXiv preprint arXiv:170606083. 2017.
204. Chen X, Liu C, Li B, Lu K, Song D. Targeted backdoor attacks on deep learning systems using data poisoning. arXiv preprint arXiv:171205526. 2017.
205. Huang H, Ma X, Erfani SM, Bailey J, Wang Y. Unlearnable examples: Making personal data unexploitable. arXiv preprint arXiv:210104898. 2021.
206. Feinman R, Curtin RR, Shintre S, Gardner AB. Detecting adversarial samples from artifacts. arXiv preprint arXiv:170300410. 2017.
207. Papernot N, McDaniel P, Wu X, Jha S, Swami A. Distillation as a defense to adversarial perturbations against deep neural networks. In: 2016 IEEE symposium on security and privacy (SP). IEEE; 2016. p. 582-97.
208. Cisse M, Bojanowski P, Grave E, Dauphin Y, Usunier N. Parseval networks: Improving robustness to adversarial examples. In: International Conference on Machine Learning. PMLR; 2017. p. 854-63.
209. Vanschoren J. Meta-learning: A survey. arXiv preprint arXiv:181003548. 2018.
210. Hospedales T, Antoniou A, Micaelli P, Storkey A. Meta-learning in neural networks: A survey. arXiv preprint arXiv:200405439. 2020.
211. Feichtenhofer C, Fan H, Xiong B, Girshick R, He K. A large-scale study on unsupervised spatiotemporal repre- sentation learning. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition; 2021. p. 3299-309.
212. He K, Fan H, Wu Y, Xie S, Girshick R. Momentum contrast for unsupervised visual representation learning. In: Proceedings of the IEEE/CVF conference on computer vision and pattern recognition; 2020. p. 9729-38.
213. Chen T, Kornblith S, Norouzi M, Hinton G. A simple framework for contrastive learning of visual representa- tions. In: International conference on machine learning. PMLR; 2020. p. 1597-607.
214. Grill JB, Strub F, Altché F, Tallec C, Richemond P, Buchatskaya E, et al. Bootstrap your own latent-a new approach to self-supervised learning. Advances in neural information processing systems. 2020;33:21271-84.
215. Caron M, Misra I, Mairal J, Goyal P, Bojanowski P, Joulin A. Unsupervised learning of visual features by contrasting cluster assignments. Advances in Neural Information Processing Systems. 2020;33:9912-24.
216. Grimson E, Wang X, Ng GW, Ma KT. Trajectory analysis and semantic region modeling using a nonparametric bayesian model. 2008.
217. i-lids–advanced video and signal-based surveillance 2007;. Available from: [http://www.eecs.qmul.ac.u](http://www.eecs.qmul.ac.uk/~andrea/avss2007_d.html) [k/~andrea/avss2007\_d.html](http://www.eecs.qmul.ac.uk/~andrea/avss2007_d.html).
218. Next Generation Simulation (NGSIM);. Available from: [https://ops.fhwa.dot.gov/trafficanalysis](https://ops.fhwa.dot.gov/trafficanalysistools/ngsim.htm) [tools/ngsim.htm](https://ops.fhwa.dot.gov/trafficanalysistools/ngsim.htm).
219. Brostow GJ, Fauqueur J, Cipolla R. Semantic object classes in video: A high-definition ground truth database. Pattern Recognition Letters. 2009;30(2):88-97.
220. Cordts M, Omran M, Ramos S, Rehfeld T, Enzweiler M, Benenson R, et al. The cityscapes dataset for semantic urban scene understanding. In: Proceedings of the IEEE conference on computer vision and pattern recognition; 2016. p. 3213-23.
221. Neuhold G, Ollmann T, Rota Bulo S, Kontschieder P. The mapillary vistas dataset for semantic understanding of street scenes. In: Proceedings of the IEEE International Conference on Computer Vision; 2017. p. 4990-9.
222. Ros G, Sellart L, Materzynska J, Vazquez D, Lopez AM. The synthia dataset: A large collection of synthetic images for semantic segmentation of urban scenes. In: Proceedings of the IEEE conference on computer vision and pattern recognition; 2016. p. 3234-43.
223. Yu F, Xian W, Chen Y, Liu F, Liao M, Madhavan V, et al. Bdd100k: A diverse driving video database with scalable annotation tooling. arXiv preprint arXiv:180504687. 2018;2(5):6.
224. De Charette R, Nashashibi F. Real time visual traffic lights recognition based on spot light detection and adaptive traffic lights templates. In: 2009 IEEE Intelligent Vehicles Symposium. IEEE; 2009. p. 358-63.
225. Mogelmose A, Trivedi MM, Moeslund TB. Vision-based traffic sign detection and analysis for intelligent driver assistance systems: Perspectives and survey. IEEE Transactions on Intelligent Transportation Systems. 2012;13(4):1484-97.
226. Houben S, Stallkamp J, Salmen J, Schlipsing M, Igel C. Detection of traffic signs in real-world images: The German Traffic Sign Detection Benchmark. In: The 2013 international joint conference on neural networks (IJCNN). IEEE; 2013. p. 1-8.
227. Timofte R, Zimmermann K, Van Gool L. Multi-view traffic sign detection, recognition, and 3D localisation. Machine vision and applications. 2014;25(3):633-47.
228. Behrendt K, Novak L, Botros R. A deep learning approach to traffic lights: Detection, tracking, and classifica- tion. In: 2017 IEEE International Conference on Robotics and Automation (ICRA). IEEE; 2017. p. 1370-7.
229. Španˇhel J, Sochor J, Juránek R, Herout A, Maršík L, Zemcˇík P. Holistic recognition of low quality license plates by CNN using track annotated data. In: 2017 14th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS). IEEE; 2017. p. 1-6.
230. L Dlagnekov SB. UCSD/Calit2 Car License Plate, Make and Model Database;.
231. Laroca R, Severo E, Zanlorensi LA, Oliveira LS, Gonçalves GR, Schwartz WR, et al. A robust real-time automatic license plate recognition based on the YOLO detector. In: 2018 international joint conference on neural networks (ijcnn). IEEE; 2018. p. 1-10.
232. Gonçalves GR, da Silva SPG, Menotti D, Schwartz WR. Benchmark for license plate character segmentation. Journal of Electronic Imaging. 2016;25(5):053034.
233. Dingus TA, Klauer SG, Neale VL, Petersen A, Lee SE, Sudweeks J, et al. The 100-car naturalistic driving study, Phase II-results of the 100-car field experiment. United States. Department of Transportation. National Highway Traffic Safety . . . ; 2006.
234. The SHRP 2 Naturalistic Driving Study;.
235. Mandal M, Kumar LK, Vipparthi SK. MOR-UAV: A Benchmark Dataset and Baselines for Moving Object Recognition in UAV Videos. arXiv. 2020.
236. Robicquet A, Sadeghian A, Alahi A, Savarese S. Learning social etiquette: Human trajectory understanding in crowded scenes. In: European conference on computer vision. Springer; 2016. p. 549-65.
237. Krajewski R, Bock J, Kloeker L, Eckstein L. The highd dataset: A drone dataset of naturalistic vehicle tra- jectories on german highways for validation of highly automated driving systems. In: 2018 21st International Conference on Intelligent Transportation Systems (ITSC). IEEE; 2018. p. 2118-25.
238. Bock J, Krajewski R, Moers T, Runde S, Vater L, Eckstein L. The inD Dataset: A Drone Dataset of Naturalistic Road User Trajectories at German Intersections. arXiv preprint arXiv:191107602. 2019.
239. Sultani W, Chen C, Shah M. Real-world anomaly detection in surveillance videos. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition; 2018. p. 6479-88.
240. NVIDIA AI CITY CHALLENGE;. Available from: <https://www.aicitychallenge.org/>.
241. Zhang S, Benenson R, Schiele B. Citypersons: A diverse dataset for pedestrian detection. In: Proceedings of the IEEE conference on computer vision and pattern recognition; 2017. p. 3213-21.
242. Free Teledyne FLIR thermal dataset for algorithm training;. Available from: [https://www.flir.com/oem/a](https://www.flir.com/oem/adas/adas-dataset-form/) [das/adas-dataset-form/](https://www.flir.com/oem/adas/adas-dataset-form/).
243. Li L, Jiang R, He Z, Chen XM, Zhou X. Trajectory data-based traffic flow studies: A revisit. Transportation Research Part C: Emerging Technologies. 2020;114:225-40.
244. Welcome to Michigan Traffic Crash Facts;. Available from: [https://www.michigantrafficcrashfacts.](https://www.michigantrafficcrashfacts.org/) [org/](https://www.michigantrafficcrashfacts.org/).
245. NASS General Estimates System;. Available from: [https://www.nhtsa.gov/national-automotive-sa](https://www.nhtsa.gov/national-automotive-sampling-system/nass-general-estimates-system) [mpling-system/nass-general-estimates-system](https://www.nhtsa.gov/national-automotive-sampling-system/nass-general-estimates-system).
246. Fatality Analysis Reporting System (FARS);. Available from: [https://www.nhtsa.gov/research-data/](https://www.nhtsa.gov/research-data/fatality-analysis-reporting-system-fars) [fatality-analysis-reporting-system-fars](https://www.nhtsa.gov/research-data/fatality-analysis-reporting-system-fars).
247. Model Minimum Uniform Crash Criteria (MMUCC);. Available from: <https://www.nhtsa.gov/mmucc-1>.
248. Sodhi M, Reimer B, Cohen J, Vastenburg E, Kaars R, Kirschenbaum S. On-road driver eye movement tracking using head-mounted devices. In: Proceedings of the 2002 symposium on Eye tracking research & applications; 2002. p. 61-8.
249. Crundall D, Underwood G. Visual attention while driving: measures of eye movements used in driving research. In: Handbook of traffic psychology. Elsevier; 2011. p. 137-48.
250. Dukic T, Broberg T. Older drivers’ visual search behaviour at intersections. Transportation research part F: traffic psychology and behaviour. 2012;15(4):462-70.
251. Kiefer P, Straub F, Raubal M. Towards location-aware mobile eye tracking. In: Proceedings of the Symposium on Eye Tracking Research and Applications; 2012. p. 313-6.
252. Yang Y, McDonald M, Zheng P. Can drivers’ eye movements be used to monitor their performance? A case study. IET Intelligent Transport Systems. 2012;6(4):444-52.
253. Lin TY, Maire M, Belongie S, Hays J, Perona P, Ramanan D, et al. Microsoft coco: Common objects in context. In: European conference on computer vision. Springer; 2014. p. 740-55.
254. Deng J, Dong W, Socher R, Li LJ, Li K, Fei-Fei L. Imagenet: A large-scale hierarchical image database. In: 2009 IEEE conference on computer vision and pattern recognition. Ieee; 2009. p. 248-55.
255. Minderhoud MM, Bovy PH. Extended time-to-collision measures for road traffic safety assessment. Accident Analysis & Prevention. 2001;33(1):89-97.
256. Mahmud SS, Ferreira L, Hoque MS, Tavassoli A. Application of proximal surrogate indicators for safety evaluation: A review of recent developments and research needs. IATSS research. 2017;41(4):153-63.
257. Wishart J, Como S, Elli M, Russo B, Weast J, Altekar N, et al. Driving Safety Performance Assessment Metrics for ADS-Equipped Vehicles. SAE Technical Paper; 2020.
258. Elli MS, Wishart J, Como S, Dhakshinamoorthy S, Weast J. Evaluation, Validation and Refinement of Opera- tional Safety Metrics for Automated Vehicles in Simulation. SAE Technical Paper; 2021.
259. Lajunen T, Summala H. Driving experience, personality, and skill and safety-motive dimensions in drivers’ self-assessments. Personality and Individual Differences. 1995;19(3):307-18.
260. Van Rooy DL, Rotton J, Burns TM. Convergent, discriminant, and predictive validity of aggressive driving inventories: They drive as they live. Aggressive Behavior: Official Journal of the International Society for Research on Aggression. 2006;32(2):89-98.
261. De Winter J, Dodou D. The Driver Behaviour Questionnaire as a predictor of accidents: A meta-analysis. Journal of safety research. 2010;41(6):463-70.
262. Zhao N, Mehler B, Reimer B, D’Ambrosio LA, Mehler A, Coughlin JF. An investigation of the relationship between the driving behavior questionnaire and objective measures of highway driving behavior. Transportation research part F: traffic psychology and behaviour. 2012;15(6):676-85.
263. Constantinou E, Panayiotou G, Konstantinou N, Loutsiou-Ladd A, Kapardis A. Risky and aggressive driving in young adults: Personality matters. Accident Analysis & Prevention. 2011;43(4):1323-31.
264. Chai J, Zhao G. Effect of exposure to aggressive stimuli on aggressive driving behavior at pedestrian crossings at unmarked roadways. Accident Analysis & Prevention. 2016;88:159-68.
265. Zhang T, Chan AH. The association between driving anger and driving outcomes: A meta-analysis of evidence from the past twenty years. Accident Analysis & Prevention. 2016;90:50-62.
266. Ge Y, Zhang Q, Zhao W, Zhang K, Qu W. Effects of trait anger, driving anger, and driving experience on dangerous driving behavior: A moderated mediation analysis. Aggressive behavior. 2017;43(6):544-52.
267. Ball L, Tully R, Egan V. The influence of impulsivity and the Dark Triad on self-reported aggressive driving behaviours. Accident Analysis & Prevention. 2018;120:130-8.
268. Tuv SS, Krabseth H, Karinen R, Olsen KM, Øiestad EL, Vindenes V. Prevalence of synthetic cannabinoids in blood samples from Norwegian drivers suspected of impaired driving during a seven weeks period. Accident Analysis & Prevention. 2014;62:26-31.
269. Jiang B, He J, Chen J, Larsen L, Wang H. Perceived Green at Speed: A Simulated Driving Experiment Raises New Questions for Attention Restoration Theory and Stress Reduction Theory. Environment and Behavior. 2020:0013916520947111.
270. Antonson H, Mårdh S, Wiklund M, Blomqvist G. Effect of surrounding landscape on driving behaviour: A driving simulator study. Journal of Environmental Psychology. 2009;29(4):493-502.
271. Antonson H, Ahlström C, Mårdh S, Blomqvist G, Wiklund M. Landscape heritage objects’ effect on driving: a combined driving simulator and questionnaire study. Accident Analysis & Prevention. 2014;62:168-77.
272. Wang L, Bie Y, Li S. The impact of roadside landscape colors on driver’s mean heart rate considering driving time. Transportation research part F: traffic psychology and behaviour. 2016;42:151-61.
273. ;. Available from: [https://www.intelligent-mobility-xperience.com/5-top-autonomous-vehicl](https://www.intelligent-mobility-xperience.com/5-top-autonomous-vehicle-companies-to-watch-in-2020-a-958065/) [e-companies-to-watch-in-2020-a-958065/](https://www.intelligent-mobility-xperience.com/5-top-autonomous-vehicle-companies-to-watch-in-2020-a-958065/).
274. Automated Driving – Levels of Driving Automation are Defined in New SAE International Standard J3016; 2014. Available from: <https://cvpr2021.wad.vision/>.
275. Administration NHTS, et al. US department of transportation releases policy on automated vehicle develop- ment. Policy. 2013:14-3.
276. Mueller AS, Cicchino JB, Zuby DS. What humanlike errors do autonomous vehicles need to avoid to maximize safety? Journal of safety research. 2020;75:310-8.
277. ;. Available from: [https://www.nbcnews.com/tech/tech-news/self-driving-uber-car-hit-kille](https://www.nbcnews.com/tech/tech-news/self-driving-uber-car-hit-killed-woman-did-not-recognize-n1079281) [d-woman-did-not-recognize-n1079281](https://www.nbcnews.com/tech/tech-news/self-driving-uber-car-hit-killed-woman-did-not-recognize-n1079281).
278. Said C. Exclusive: Tempe police chief says early probe shows no fault by Uber. San Francisco Chronicle; 2018.
279. Singh R, Ayyar MP, Pavan TVS, Gosain S, Shah RR. Automating Car Insurance Claims Using Deep Learning Techniques. In: 2019 IEEE Fifth International Conference on Multimedia Big Data (BigMM). IEEE; 2019. p. 199-207.
280. Konrardy B, Christensen ST, Hayward G, Farris S. Fully autonomous vehicle insurance pricing. Google Patents; 2019. US Patent 10,373,259.
281. Bowne BF, Baker NR, Marzinzik DL, Riley ME, Christopulos NU, Fields BM, et al.. Methods to determine a vehicle insurance premium based on vehicle operation data collected via a mobile device. Google Patents; 2019. US Patent 10,402,907.
282. Pooja P, Hariharan B. An early warning system for traffic and road safety hazards using collaborative crowd sourcing. In: 2017 International Conference on Communication and Signal Processing (ICCSP). IEEE; 2017. p. 1203-6.
283. Allen FV. Google Maps Now Features Real-time Crowdsourced Accident Info; 2013. Available from: [https://www.techlicious.com/blog/google-maps-now-features-real-time-crowdsourc](https://www.techlicious.com/blog/google-maps-now-features-real-time-crowdsourced-accident-info/) [ed-accident-info/](https://www.techlicious.com/blog/google-maps-now-features-real-time-crowdsourced-accident-info/).
284. Khan WZ, Ahmed E, Hakak S, Yaqoob I, Ahmed A. Edge computing: A survey. Future Generation Computer Systems. 2019;97:219-35.
285. Liu S, Liu L, Tang J, Yu B, Wang Y, Shi W. Edge computing for autonomous driving: Opportunities and challenges. Proceedings of the IEEE. 2019;107(8):1697-716.
286. Yu W, Liang F, He X, Hatcher WG, Lu C, Lin J, et al. A survey on the edge computing for the Internet of Things. IEEE access. 2017;6:6900-19.
287. Raza S, Wang S, Ahmed M, Anwar MR. A survey on vehicular edge computing: architecture, applications, technical issues, and future directions. Wireless Communications and Mobile Computing. 2019;2019.
288. Hu Z, Zheng Z, Wang T, Song L, Li X. Roadside unit caching: Auction-based storage allocation for multiple content providers. IEEE Transactions on Wireless Communications. 2017;16(10):6321-34.
289. Su Z, Hui Y, Xu Q, Yang T, Liu J, Jia Y. An edge caching scheme to distribute content in vehicular networks. IEEE Transactions on Vehicular Technology. 2018;67(6):5346-56.
290. Mahmood A, Casetti C, Chiasserini CF, Giaccone P, Harri J. Mobility-aware edge caching for connected cars. In: 2016 12th Annual Conference on Wireless On-demand Network Systems and Services (WONS). IEEE; 2016. p. 1-8.
291. Liu Y, Wang S, Huang J, Yang F. A computation offloading algorithm based on game theory for vehicular edge networks. In: 2018 IEEE International Conference on Communications (ICC). IEEE; 2018. p. 1-6.
292. Du J, Yu FR, Chu X, Feng J, Lu G. Computation offloading and resource allocation in vehicular networks based on dual-side cost minimization. IEEE Transactions on Vehicular Technology. 2018;68(2):1079-92.
293. Deng DJ, Lien SY, Lin CC, Hung SC, Chen WB. Latency control in software-defined mobile-edge vehicular networking. IEEE Communications Magazine. 2017;55(8):87-93.
294. Jia D, Lu K, Wang J, Zhang X, Shen X. A survey on platoon-based vehicular cyber-physical systems. IEEE communications surveys & tutorials. 2015;18(1):263-84.
295. Liu L, Chen C, Pei Q, Maharjan S, Zhang Y. Vehicular edge computing and networking: A survey. Mobile Networks and Applications. 2020:1-24.
296. Chen Z, He Q, Mao Z, Chung HM, Maharjan S. A study on the characteristics of douyin short videos and implications for edge caching. In: Proceedings of the ACM Turing Celebration Conference-China; 2019. p. 1-6.
297. Grassi G, Jamieson K, Bahl P, Pau G. Parkmaster: An in-vehicle, edge-based video analytics service for detecting open parking spaces in urban environments. In: Proceedings of the Second ACM/IEEE Symposium on Edge Computing; 2017. p. 1-14.
298. Park HS, Park MW, Won KH, Kim KH, Jung SK. In-vehicle AR-HUD system to provide driving-safety infor- mation. ETRI journal. 2013;35(6):1038-47.
299. Cheng HT, Shan H, Zhuang W. Infotainment and road safety service support in vehicular networking: From a communication perspective. Mechanical systems and signal processing. 2011;25(6):2020-38.
300. Hulshof W, Knight I, Edwards A, Avery M, Grover C. Autonomous emergency braking test results. In: Pro- ceedings of the 23rd International Technical Conference on the Enhanced Safety of Vehicles (ESV). National Highway Traffic Safety Administration Washington, DC; 2013. p. 1-13.
301. Eichelberger AH, McCartt AT. Toyota drivers’ experiences with dynamic radar cruise control, pre-collision system, and lane-keeping assist. Journal of safety research. 2016;56:67-73.
302. Östling M, Lubbe N, Jeppsson H, Puthan P. Passenger car safety beyond ADAS: Defining remaining accident configurations as future priorities. In: The 26th International Technical Conference on the Enhanced Safety of Vehicles, Eindhoven, Netherlands; 2019. p. 19-0091.
303. Sternlund S, Strandroth J, Rizzi M, Lie A, Tingvall C. The effectiveness of lane departure warning systems—A reduction in real-world passenger car injury crashes. Traffic injury prevention. 2017;18(2):225-9.
304. A Breakthrough Preview: JIDU Auto Debuts Intelligent Robo-01 Concept Vehicle, Powered by NVIDIA DRIVE Orin; 2022. Available from: [https://blogs.nvidia.com/blog/2022/06/14/jidu-robo-01-](https://blogs.nvidia.com/blog/2022/06/14/jidu-robo-01-concept-vehicle-drive-orin/) [concept-vehicle-drive-orin/](https://blogs.nvidia.com/blog/2022/06/14/jidu-robo-01-concept-vehicle-drive-orin/).
305. Smart Utility Vehicle: NIO ES7 Redefines Category with Intelligent, Versatile EV Powered by NVIDIA DRIVE Orin; 2022. Available from: [https://blogs.nvidia.com/blog/2022/06/16/nio-es7-intelligent-e](https://blogs.nvidia.com/blog/2022/06/16/nio-es7-intelligent-ev-drive-orin/) [v-drive-orin/](https://blogs.nvidia.com/blog/2022/06/16/nio-es7-intelligent-ev-drive-orin/).
306. Going Nowhere Fast? Smart Traffic Lights Can Help Ease Gridlock; 2022. Available from: [https://scienc](https://science.howstuffworks.com/engineering/civil/smart-traffic-lights-news.htm) [e.howstuffworks.com/engineering/civil/smart-traffic-lights-news.htm](https://science.howstuffworks.com/engineering/civil/smart-traffic-lights-news.htm).
307. St-Aubin P, Miranda-Moreno L, Saunier N. An automated surrogate safety analysis at protected highway ramps using cross-sectional and before–after video data. Transportation Research Part C: Emerging Technologies. 2013;36:284-95.
308. Yan X, Abdel-Aty M, Radwan E, Wang X, Chilakapati P. Validating a driving simulator using surrogate safety measures. Accident Analysis & Prevention. 2008;40(1):274-88.
309. Mullakkal-Babu FA, Wang M, He X, van Arem B, Happee R. Probabilistic field approach for motorway driving risk assessment. Transportation Research Part C: Emerging Technologies. 2020;118:102716.
310. Chen P, Zeng W, Yu G, Wang Y. Surrogate safety analysis of pedestrian-vehicle conflict at intersections using unmanned aerial vehicle videos. Journal of advanced transportation. 2017;2017.
311. Saunier N, Miranda-Moreno LF. Road user collision prediction using motion patterns applied to surrogate safety analysis. 2014.
312. Hao P, Sun Z, Ban XJ, Guo D, Ji Q. Vehicle index estimation for signalized intersections using sample travel times. Transportation Research Part C: Emerging Technologies. 2013;36:513-29.
313. Shahdah U, Saccomanno F, Persaud B. Integrated traffic conflict model for estimating crash modification factors. Accident Analysis & Prevention. 2014;71:228-35.
314. Hoogendoorn RG, van Arem B, Brookhuis KA. Longitudinal driving behavior in case of emergency situations: an empirically underpinned theoretical framework. Transportation research part C: emerging technologies. 2013;36:581-603.
315. Zheng L, Ismail K, Meng X. Freeway safety estimation using extreme value theory approaches: A comparative study. Accident Analysis & Prevention. 2014;62:32-41.
316. Kuang Y, Qu X, Wang S. A tree-structured crash surrogate measure for freeways. Accident Analysis & Preven- tion. 2015;77:137-48.
317. Huang H, Wang D, Zheng L, Li X. Evaluating time-reminder strategies before amber: Common signal, green flashing and green countdown. Accident Analysis & Prevention. 2014;71:248-60.
318. Kim I, Kim T, Sohn K. Identifying driver heterogeneity in car-following based on a random coefficient model. Transportation research part C: emerging technologies. 2013;36:35-44.
319. Wu KF, Aguero-Valverde J, Jovanis PP. Using naturalistic driving data to explore the association between traffic safety-related events and crash risk at driver level. Accident Analysis & Prevention. 2014;72:210-8.
320. Lv Y, Duan Y, Kang W, Li Z, Wang FY. Traffic flow prediction with big data: a deep learning approach. IEEE Transactions on Intelligent Transportation Systems. 2014;16(2):865-73.
321. Zhao Z, Chen W, Wu X, Chen PC, Liu J. LSTM network: a deep learning approach for short-term traffic forecast. IET Intelligent Transport Systems. 2017;11(2):68-75.
322. Polson NG, Sokolov VO. Deep learning for short-term traffic flow prediction. Transportation Research Part C: Emerging Technologies. 2017;79:1-17.
323. Yu B, Yin H, Zhu Z. Spatio-temporal graph convolutional networks: A deep learning framework for traffic forecasting. arXiv preprint arXiv:170904875. 2017.
324. Wu Y, Tan H, Qin L, Ran B, Jiang Z. A hybrid deep learning based traffic flow prediction method and its understanding. Transportation Research Part C: Emerging Technologies. 2018;90:166-80.
325. Mozaffari S, Al-Jarrah OY, Dianati M, Jennings P, Mouzakitis A. Deep learning-based vehicle behaviour pre- diction for autonomous driving applications: A review. arXiv preprint arXiv:191211676. 2019.
326. Duan Y, Lv Y, Liu YL, Wang FY. An efficient realization of deep learning for traffic data imputation. Trans- portation research part C: emerging technologies. 2016;72:168-81.
327. Wang Z. The applications of deep learning on traffic identification. BlackHat USA. 2015;24(11):1-10.
328. Žbontar J, LeCun Y. Stereo matching by training a convolutional neural network to compare image patches.

The journal of machine learning research. 2016;17(1):2287-318.

1. Luo W, Schwing AG, Urtasun R. Efficient deep learning for stereo matching. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition; 2016. p. 5695-703.
2. Fischer P, Dosovitskiy A, Ilg E, Häusser P, Hazırbas¸ C, Golkov V, et al. FlowNet: Learning Optical Flow with Convolutional Networks. arXiv. 2015.
3. Ranjan A, Black MJ. Optical Flow Estimation Using a Spatial Pyramid Network. 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). 2017:2720-9.
4. ; 2020. Available from: <https://www.tesla.com/autopilot>.
5. Vassiliades A, Bassiliades N, Patkos T. Argumentation and explainable artificial intelligence: a survey. The Knowledge Engineering Review. 2021;36.
6. Ribeiro MT, Singh S, Guestrin C. " Why should i trust you?" Explaining the predictions of any classifier. In: Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining; 2016. p. 1135-44.
7. Schlegel U, Vo DL, Keim DA, Seebacher D. Ts-mule: Local interpretable model-agnostic explanations for time series forecast models. In: Joint European Conference on Machine Learning and Knowledge Discovery in Databases. Springer; 2021. p. 5-14.
8. Meske C, Bunde E. Transparency and trust in human-AI-interaction: The role of model-agnostic explanations in computer vision-based decision support. In: International Conference on Human-Computer Interaction. Springer; 2020. p. 54-69.
9. ;. Available from: <https://az511.gov/>.
10. Office of Highway Policy Information;. Available from: [https://www.fhwa.dot.gov/policyinformati](https://www.fhwa.dot.gov/policyinformation/statistics/2017/hm60.cfm) [on/statistics/2017/hm60.cfm](https://www.fhwa.dot.gov/policyinformation/statistics/2017/hm60.cfm).
11. Chakraborty A, Alam M, Dey V, Chattopadhyay A, Mukhopadhyay D. Adversarial attacks and defences: A survey. arXiv preprint arXiv:181000069. 2018.
12. Creating the autonomous future takes experience and vision; 2022. Available from: [https://www.mobileye](https://www.mobileye.com/)

[.com/](https://www.mobileye.com/).

1. CES 2020: Engines Powering L2+ to L4 (Mobileye); 2020. Available from: [https://s21.q4cdn.com/6006](https://s21.q4cdn.com/600692695/files/doc_presentations/2020/1/Mobileye-CES-2020-presentation.pdf) [92695/files/doc\_presentations/2020/1/Mobileye-CES-2020-presentation.pdf](https://s21.q4cdn.com/600692695/files/doc_presentations/2020/1/Mobileye-CES-2020-presentation.pdf).
2. Omniverse platform for Virtual Collaboration. NVIDIA;. Available from: [https://www.nvidia.com/en-us](https://www.nvidia.com/en-us/omniverse/)

[/omniverse/](https://www.nvidia.com/en-us/omniverse/).

1. Self-driving cars technology: Solutions from Nvidia Automotive. NVIDIA;. Available from: [https://www.](https://www.nvidia.com/en-us/self-driving-cars/) [nvidia.com/en-us/self-driving-cars/](https://www.nvidia.com/en-us/self-driving-cars/).
2. Why Is Tesla’s Full Self-Driving Only Level 2 Autonomous?; 2021. Available from: [https:](https://www.forbes.com/sites/jamesmorris/2021/03/13/why-is-teslas-full-self-driving-only-level-2-autonomous/?sh=5c45367c6a32)

[//www.forbes.com/sites/jamesmorris/2021/03/13/why-is-teslas-full-self-driving-on](https://www.forbes.com/sites/jamesmorris/2021/03/13/why-is-teslas-full-self-driving-only-level-2-autonomous/?sh=5c45367c6a32) [ly-level-2-autonomous/?sh=5c45367c6a32](https://www.forbes.com/sites/jamesmorris/2021/03/13/why-is-teslas-full-self-driving-only-level-2-autonomous/?sh=5c45367c6a32).

1. Ersoy S, Waqar T. Autonomous Vehicle and Smart Traffic; 2020.
2. Ranka S, Rangarajan A, Elefteriadou L, Srinivasan S, Poasadas E, Hoffman D, et al. A vision of smart traf- fic infrastructure for traditional, connected, and autonomous vehicles. In: 2020 International Conference on Connected and Autonomous Driving (MetroCAD). IEEE; 2020. p. 1-8.
3. Bloom C, Tan J, Ramjohn J, Bauer L. Self-driving cars and data collection: Privacy perceptions of networked autonomous vehicles. In: Thirteenth Symposium on Usable Privacy and Security (SOUPS 2017); 2017. p. 357-75.
4. Banks VA, Plant KL, Stanton NA. Driver error or designer error: Using the Perceptual Cycle Model to explore the circumstances surrounding the fatal Tesla crash on 7th May 2016. Safety science. 2018;108:278-85.