A Progressive Review: Emerging Technologies for ADAS Driven Solutions

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***Abstract*—Over the last decade, the Advanced Driver Assistance System (ADAS) concept has evolved significantly. ADAS involves several technologies such as automotive electronics, vehicle-to-vehicle (V2V) vehicle-to-infrastructure (V2I) communication, RADAR, LIDAR, computer vision, and machine learning. Of these, *computer vision* and *machine learning* based solutions have mainly been effective that have allowed real-time vehicle control, driver aided systems, etc. However, most of the existing works deal with the deployment of ADAS and autonomous driving functionality in countries with well-disciplined lane traffic. Nevertheless, these solutions and frameworks do not work in countries and cities with less-disciplined/chaotic traffic. This paper identifies the research gaps, reviews the state-of-the-art looking at the different functionalities of ADAS and its levels of autonomy. Importantly, it provides a detailed description of vision intelligence and computational intelligence for ADAS. The eye-gaze and head pose estimation in vision intelligence is detailed. Notably, the learning algorithms such as supervised, unsupervised, reinforcement learning and deep learning solutions for ADAS are considered and discussed. Significantly, this would enable developing a real-time recommendation system for system-assisted/autonomous vehicular environments with less-disciplined road traffic.**

***Index Terms*—Autonomous driving, computer vision, intelligent transportation, machine learning, multi-sensor.**

I. Introduction

A SIGNIFICANT concern in the transportation sector is the massive number of road accidents and health-related issues in the present-day world. As per the World Health Organization (WHO) estimation, the number of road accidents annually is approximately 1.34 million, with nearly 50 million injuries globally [1]. According to WHO, road fatalities are the 9^{th} most significant cause of death/fatalities. Notably, dealing with dense traffic in an inadequate and insufficient urban road traffic infrastructure is highly challenging. It is anticipated that by 2023, the number of fatal accidents would increase and could move to 6^{th} place [2].

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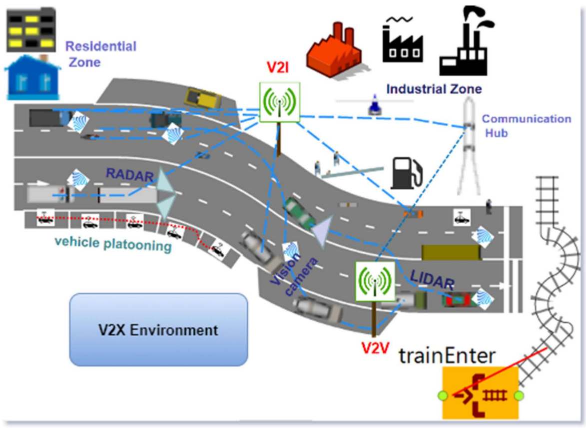

Fig. 1. Illustration of various sensing and communication mechanisms for V2X environments - towards ADAS.

Over the last decade, there has been extensive work in the area of autonomous and self-driving vehicles. However, most of these solutions cater to roads in developed countries where the vehicles follow lane discipline. Notably, there is minimal traffic discipline even on main roads in many countries and cities worldwide, especially southeast Asia, Africa, etc. Hence, autonomous driving is still a far-reaching challenge in these places. In fact, as per the autonomous levels defined by the Society of Automotive Engineers (SAE), most of the designers and developers of ADAS solutions still have to focus on L2/L3 levels of autonomy; in less-disciplined/chaotic lane traffic scenarios. One of the biggest challenges in the next decade of road transportation would be vehicles with different levels of autonomy (L2 to L5). Further, given the heterogeneity in the vehicular model and capabilities, it is imperative to understand the presence of other vehicles in the immediate neighborhood. Secondly, it is essential to obtain information on different factors such as traffic density, detection of different objects, the proximity of other vehicles on all sides etc. Thirdly, it is crucial to have a complete visual picture of the road and traffic environment. These can be achieved using different sensing mechanisms such as cameras, RADAR, LIDAR, GPS; through V2X (vehicle to anything) and wireless communication. An illustration of multi-modal sensing mechanisms that are essentially involved in system-assisted road traffic scenarios is shown in Fig. 1. The following subsection provides a detailed description of different sensing mechanisms for dynamic information exchange among the neighboring vehicles in the traffic environment.

A. V2V/V2X Communication

Vehicular technology transmits the information collected from the different sensors to neighboring vehicles [3]. It uses the dedicated short-range communication (DSRC) channel for information exchange [4]–[6]. Further, in a very recent work [7], the authors investigated the control problem for leader-following vehicle platoons using VANETS with variation in the communication ranges. Typically, vehicular communication is categorized based on active and passive systems. This involves real-time applications [8], [9] such as *collision warning*, *lane assistance* and *emergency braking system*.

B. RADAR

RADAR is based on radio detection and ranging. Further, it is used to compute the neighboring vehicle's location, range, and velocity bidirectionally. RADAR consumes lighter processing resources comparatively with alternative sensor mechanisms and works in varied climatic situations [10], [11].

C. LIDAR

LIDAR is based on light detection and ranging. LIDAR computes the relative distance to an ego obstacle considering the time taken by a light source range to an ego object and vice-versa. Most of the recent applications of LIDAR for self-driven vehicles are proposed in [12], [13]. However, LIDAR is expensive compared to RADAR.

D. Camera Sensors

A combination of visible and infrared (IR) cameras would effectively capture environment information, thereby resulting in a better analysis of different driving environments with different climatic conditions. Monocular cameras make use of image sensing components such as Charge-Coupled Devices (CCD) or the complementary metal-oxide-semiconductor (CMOS) [14]. The IR camera [15] sensing mechanism works for IR wavelengths ranging from 780 nm to 1 mm. The stereo vision camera sensors like *scenescan* [16] have two lenses that help in accurate 3D depth estimation of scenes in challenging situations. The development and advances of such systems are accomplished with advanced vision-based solutions for complete geometric and photo-metric visual cues that help in scene understanding.

Different combinations of active and passive sensors are used to perform the two main perception tasks in autonomous vehicles.

1) Environmental Perception: vehicle detection and tracking, pedestrian detection, road surface, road lane detection, and road sign detection are all done with RGB cameras, thermal cameras, LIDAR, and RADAR.
2) Localization: The relative and absolute positions of the vehicle are determined using global navigation satellite systems (GNSS), inertial measurement units (IMU), inertial navigation systems (INS), odometers, cameras and LIDAR.

Table I illustrates multi-modal sensors for ADAS with detailed comparison. However, there are several limitations in particular when these sensors are individually used without integrating them. Using only one particular sensor limits their functioning towards accurate and reliable predictions or detecting obstacles in varied climatic environments and illumination challenges. In this regard, cost-effective, reliable and multi-sensor fusion-based mechanisms need to be developed to leverage the benefits of advanced driver assistance systems. A fusion of multiple sensors is investigated in detail considering various parameters, applications, advantages and is discussed in Table II. This work aims to comprehensively review the state-of-the-art approaches for sensor fusion, decision control in ADAS and identify the research gaps. Importantly, this paper focuses on various research artifacts involving computer vision, machine learning, and deep learning for autonomous driving/system-assisted driving environments to assist the driver in less-disciplined/chaotic traffic environment.

The paper is arranged as follows: Section II focuses on ADAS features and functionalities, autonomy levels, emerging research gaps, and benchmark data sets with detailed comparison. Section III describes the technological requirements of ADAS, detailing vision-based intelligence for intelligent transportation. Section IV describes the different machine learning and deep learning techniques providing a systematic review of advanced techniques. Finally, Section V concludes this paper.

II. Advanced Driver Assistance System - ADAS

ADAS plays a major role in real-time driver assistance by repeatedly warning the driver or operating the vehicle's control systems, improving vehicle safety. ADAS system alerts the traffic drivers with sufficient road traffic information that could help them to reduce the traffic way-point congestion increasing the visibility of navigating road area [41]. Essentially, ADAS helps with traffic analysis and monitoring mechanisms in an intelligent transportation system (ITS) to facilitate real-time traffic control and safety applications. Subsequently, such design and development would enhance the driving efficiency with safety measures among the diverse traffic participants [42]. An ADAS system would enable core safety applications that include automatic speed adopting with acceleration/deceleration control mechanism, lane departure assistance, collision alerts, blind-spot monitoring systems of vehicles [43], [44]. Features such as anti-locking Braking System (ABS), Stability control, etc. help in avoiding the accidents [45]. Safety is one of the main thrusts behind the evolution, standardization, execution and advancement of ITS frameworks [46]. Through numerous research interests such as *communication, computer vision, control systems, electronics* and *vehicle dynamics*, ITS aims to increase the safety and efficiency of road transportation systems [47]. ITS services are based on sharing of common technical functionalities and organizational perspective [48]. The existing prototypes have been built adhering to the different levels of

TABLE I
COMPARISON OF MULTIPLE SENSORS FOR ADAS

Sensor Type	Functioning	Limitations	Data Collection	Range	Sensitivity	Accuracy
RADAR	Cloudy weather conditions, and at night. Longer operating distance and range coverage.	Precise image of an object given longer wavelength.	77GHz 79GHz	0.5 to 20 mts 1 to 60 mts 10 to 250 mts	Detecting small objects	Good
LIDAR	Suitable for both short- and long-range use.	Affected by stability of wavelength	905nm 1550nm	~200 m coverage	Detecting in fog, snow and rain	Good
Camera	Detects the objects. Works for blind spots, parking assist, lane keeping, traffic sign	may not detect tiny objects. Occlusions, illumination Requires calibration.	12.5Hz	~50m - 100m	High to varied colors Less depth estimation	Moderate
NIR	Detects objects in night Detecting objects under illuminations	low resolution and lacks in detecting objects in vehicle	~30Hz TIFF JPEG	~0.75-1.7m	Limits to shorter than ~2.5 m	Good
GPS	Mapping, positioning and navigation State estimation of vehicle	Issues in forest areas environmental conditions	Longitude Latitude Time Distance	~sync to satellite time	lowest signal level not possible to track	Good ~till 4.9m
Ultrasonic	Sound waves to find obstacle, sends back echos	Restricted use at low speeds	~346 m/s.	up to 5.5 m	Balanced signal strength	Good Shorter distances

TABLE II
MULTI-SENSOR FUSION FOR AUTONOMOUS DRIVING

S.No	Multi-Sensor Fusion	Without Fusion Limitations	With Fusion Benefits	Applications
1	Vision and LiDAR	Sensitive to lighting quality LiDAR 3D scene reconstruction resolution is low when used alone.	Measure depth and range, Less computational power; Challenging weather conditions (fog and rain)	People detection Scene perception
2	Vision and Infrared	Only with a vision camera can you see at night; Thermal sensors miss finer object details	Handles illumination challenges Operates well in varied climatic conditions	People detection Scene perception Night vision
3	Vision and LiDAR	Lighting and illumination conditions High computational costs for depth measurements LiDAR measurements: limited resolution and range Sparse point cloud LiDAR data	Calibration of scattered LiDAR point cloud, Road geometry (depth)	Road detection Path planning
4	Vision and Radar	Low resolution of radar Require special lenses heavy computation to measure distance.	Accurate distance measuring Detects well in bad weather	Obstacle detection Road lane analysis
5	Vision and IMU	llumination issues Camera blurring problem Drifting error for IMU	Better accuracy Low computational overhead Less vision noise, Limited error in IMU drifts	Path planning Trajectory estimation Mapping Localization

autonomy as defined by SAE [49]. The next subsection details the core functionalities of ADAS along with the state-of-the-art work and research gaps.

A. Core Functionalities of ADAS

The ADAS features are classified based on levels of autonomy as shown below.

1) L1- Adaptive cruise control, parking assist.
2) L2 - Auto-steering control, lane keep assist, lane departure warning, traffic jam and blind-spot assist.
3) L3 - Highway patrol, intersection pilot, driver assist.
4) L4 - Conditional automated driving.
5) L5 - Fully Autonomous.

The ADAS features based on levels of autonomy can be further categorized, analyzed based on their advancements and complexity and is shown in Fig. 2.

ADAS features: This subsection discusses in detail on core features of ADAS, highlighting the possible research gaps.

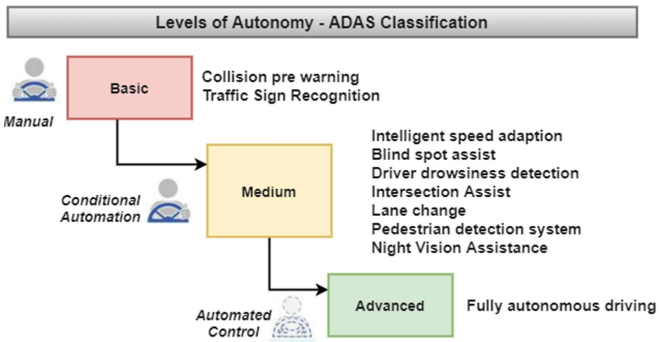

Fig. 2. Classification of ADAS features - SAE levels of autonomy.

1) Collision Avoidance System (Pre-Crash): The adequate functioning of collision avoidance depends on the speed of the vehicle. Braking is a frequently occurring mechanism for low-speed vehicles (< 50 km/hr). Vehicles with collision avoidance alert mechanisms sometimes also potentially have an adaptive cruise control integrated with front-looking sensors [50], [51]. The Collision Avoidance Systems avoid/reduce road fatalities through advanced sensing capabilities such as warning mechanisms. Traditional solutions such as collision avoidance constrained filtering, communication and reliability are referred to in [52]–[54]. However, designing such systems, especially for less lane discipline traffic as seen in developing nations such as South-East Asia, Africa is highly challenging in identifying the objects when traveling at higher speeds.

Research Gaps: Predicting headway time of vehicles much before the event, developing a protocol for Vehicular communication for controlling rear-vehicle end collisions are the two main research gaps.

2) Traffic Sign Recognition: These systems localize and identify the traffic signboards and alert drivers on the road to take necessary actions. The usage of such a process would be to locate the speed limit from the signboard by examining the input video data and adjusting the speed of the vehicle [55]. Improvements to driver safety with fast data collection and interpretation of different traffic signs are discussed in [56], [57] with advanced machine learning algorithms.

Research Gaps:

1) Address illuminations, occlusions and view angle.
2) Handling motion artifacts.
3) Damaged or partially obscured sign.
4) Poor traffic sign localization accuracy.

3) Intelligent Speed Adaption (ISA): ISA systems are modeled to verify and alert the vehicle based on varying speed zones such as highways, inner-city traffic-driving scenarios [58]. However, evaluating the impact of deploying speed adapting systems for chaotic road traffic requires great efforts due to the uneven nature of traffic. Wang *et al.* [59] proposed a data-driven approach for predicting the driver's take-over readiness state based on in-vehicle vision sensors using the LSTM model. The bi-directional LSTM model is proposed and compared with other benchmark models. Boukerche *et al.* in [60] presented a study on using machine learning for smart transportation. In particular, the mathematical modeling, parametric and non-parametric methods were compared. Nawaf *et al.* in [61], presented a study on various Data Mining and Machine Learning Techniques for control systems and ITS.

Research Gaps: Vehicular behavioral analysis based on artifacts such as inertial navigation sensor systems for rural, semi-urban, heterogeneous road traffic conditions.

4) Blind Spot Monitor: Blind spots are areas outside of a vehicle that the driver is unable to see. The blind-spot monitoring essentially works with a vehicle embedded with sensors that would sense neighbor vehicles across the driver's side view and rear views paths. It also includes the *Cross/Junction Traffic Alerts* for drivers moving out from parking space when traffic entities such as vehicles are passing from the sides [62]. Existing systems like sideEye [63] monitor the blind spot and alerts the driver. Traditional solutions providing the blind-spot assistance include [64]–[67]. However, developing systems demands better processing speed with limited computational overheads.

The authors in [68], proposed new lightweight architecture with neural network techniques towards transferring the blind spot detection to a classification task. Notably, they compared VGG, depth-wise separable network, resnets and squeeze-nets with limited parameters. Separable conv-nets with resnet performed better with 97.58% detection accuracy with inference time of 0.00159 sec on 10,000 annotated images captured with the blind spot view camera fixed on the vehicle. Further, for night-time blind-spot detection, the authors in [69] proposed a framework to transform day to night artificial images using GAN. Significantly, multiple datasets such as Nexar, Genesis and Sonata having nearly 10 K images were evaluated and achieved 97% precision. Additionally, more advanced methods have been proposed and patented in [70], [71] for better control and visualization of blind spots.

Research Gaps: There are still unsolved issues such as changing position, orientation, varied lighting conditions, etc. In existing studies, drowsiness-motivated driving sequences are considered and lack safe alerts or warnings based on the driving patterns. Also, most blind-spot monitoring systems do not reliably detect motorcyclists and bicyclists.

5) Driver Drowsiness and Distraction Detection: Driver drowsiness and fatigue monitoring are two main factors to be considered in avoiding vehicle accidents. These factors assist the driver in immediate response to avoid situations like inattentiveness while driving, more extended latency period and an increased risk of accidents [72]. Alshaqaqi *et al.* [73] discussed a new, improved module for calculation of the symmetry in face detection and eye localization. Additionally, the driver fatigue detection system verifies if the driver is distracted from his/her attention while driving based on their 3D facial expressions and eye gaze movements. The driver distraction monitoring and analysis on eyelid movements with tracking and image-based difference mechanisms were discussed in [74], [75]. In [76], the authors discussed eye detection-based driver distraction analysis and evaluated on ZJU eye blink dataset achieving 99.8% AUC score. Hu *et al.* [77] proposed a 3D convolutional GAN with two-phase Bi-LSTM for drowsiness recognition. Notably, NTHU-DDD dataset was used for evaluation and and accuracy rate (AR) of 91.2% was obtained. The authors in [78], briefly discussed a comprehensive view of cognitive parameters of driver deviation from conservative nature while driving.

In particular, for driver drowsiness monitoring, it is also imperative to analyze the driver's influential cognitive parameters in-vehicle. Typically this includes distraction, deviation, haze etc. Notably, the cognitive aspects of a driver could be investigated considering parameters such as front facial patterns [79], eye gaze estimation [80]–[82] etc. However, this requires correspondence matching of multi-modal and multi-sensor information collected in real-time driving. Measuring the cognitive load [83]–[85] of a driver not only helps in assisting but also avoids the risk of collision. A notable research direction that could be addressed is fusing the multi-sensor data (RGB and thermal) and estimate the driver inattention with cognitive load.

Research Gaps: There are still unsolved issues such as changing position, orientation, varied lighting conditions, etc. In existing studies, drowsiness-motivated driving sequences are mostly considered and lack safe alerts or warnings based on the driving patterns.

6) Intersection Assistant: Intersection assistant systems investigate any cross traffic in intersecting trajectories/complex road traffic junctions. These systems detect dangerous scenarios; warn the driver with audio-visual warnings and automatically apply brakes [86]. This system monitors the mixed traffic for any road intersections. The works in [87], [88] discussed the intersection assistance mechanisms based on background segmentation with oriented bounding boxes and blob level tracking for finding important intersections. Further, the authors in [89] proposed a model to study the driver's navigation, particularly at intersections, with an IMM goal intent classification algorithm.

Research Gaps: Lack of design tracking schemes to deal with occlusion and cluttered scenarios in complex intersections in semi-urban road environments.

7) Lane Change Assistance: It uses camera/multi-vision sensor systems to perceive the lane markings and detect the lane deviations in the road traffic environment. Further, it assists the driver in preventing the vehicle from deviating the lane [90]. Butakov [91] presented a technique that preserves the driving action units of an individual driver/vehicle response before and while in the lane changing situation under different naturalistic driving behaviors. Ko *et al.* in [92] proposed a solution that yields salient points on the lanes and projects a clustering approach for key points as segmentation for point clouds. The proposed model is evaluated on the Tusimple dataset with 96.7% accuracy. Subsequently, the work in [93] proposed a lane edge monitoring network to detect salient points along the lane boundaries. Typically, this involved inverse perspective transformation with geometric primitives.

Research Gaps:

1) Occlusion conditions of road lane.
2) Real time tracking in cast shadows.
3) Variable ambient illumination condition.
4) Develop advanced LSTM networks with driver profiling to provide assistance in curved roads.

8) Pedestrian Protection System: Pedestrian protection system detects the pedestrians moving on the road and alerts the driver in real-time. Vehicle-mounted sensors are used for the detection of pedestrians. However, the main disadvantage is that the visibility of vehicles is limited. Hence, advanced systems with sensors are required for monitoring traffic and sending appropriate signals to the vehicle [94]. Different pedestrian detection mechanisms were discussed in [95]–[97] with the comparison of various sensing mechanisms. The Bayesian frameworks and statistical geometric structure modeling was experimented on KITTI and INRIA datasets. Chen in [98] proposed a pedestrian detection system and modeled it with multi-spectral cameras. Significantly, it achieved 9% log-average miss rate (LAMR) evaluated on the WPI pedestrian dataset. Further, in [99], the authors introduce a 16-bit thermal dataset ZUT and model with YOLO V3 and CAN bus acquiring 89% mAP.

Research Gaps: The different open areas include:

1) High variability in appearance of pedestrians.
2) Detecting the occluded pedestrians in urban traffic.
3) To develop a Pedestrian detection system for night time addressing varied illumination and reflection challenges.

9) Night vision: The main objective of automotive night vision systems is to improve the driver's perception, especially beyond the area covered by the vehicle headlights. In most of the existing solutions, an objective lens focuses with available light (photons) on the photo-cathode of an image intensifier [100]. Current sensor mechanisms for near-infrared (NIR) are based on CCD or CMOS technology. Far infrared (FIR)/thermographic cameras (FIR) are based on semiconductors cooled by Peltier elements. Based on their thermal signature, FIR night vision assistance can also detect living creatures. The Night Vision system examines the information of the scene while considering the motion of the vehicle [101]. The authors in [102] proposed a structure-based unpaired image-to-image translation approach. Also, it is observed that the training samples do not restrict the domain adjustment nature of object detection. Potentially, two algorithms, Faster R-CNN and YOLO performances, have been investigated. Venator *et al.* [103] proposed a collaborative acquisition of camera images for the synthesis of image sequences from arbitrary road sections. These help to reconstruct the camera viewpoints, further robustly preserving the image registration.

Research Gaps:

1) Lack of system dealing with resolution conflicts. 53
2) Develop a system to alter and improve ion film that restricts the number of electrons passing through, increasing the halo effect.
3) Short and long-range distances and inclement weather conditions.

B. Vehicular Motion Control for ADAS

Vehicular motion controlling is necessary either through manual or system-assisted mechanisms considering parameters such as velocity, kinematics, vehicle dynamics. Notably, a fusion of algorithms/ models/ simulation works has been proposed in the prior art [104], [105] for vehicle control. It is imperative to introduce controlling systems for applications such as Adaptive cruise control, lane deviation, collision pre-warning etc. However, most existing works depend on a few parameters such as velocity, speed, GPS etc. However, when it comes to the real-time environment, the control frameworks need to be dynamic, cooperative [106] to be used in applications such as intelligent speed adaption and operational control of vehicles.

C. Data-Sets and Benchmark Challenges for ADAS

The fundamental techniques for autonomous vehicles include solving numerous tasks such as - three-dimensional scene reconstruction, localization based on different external road environment factors, etc. However, the lack of a more comprehensive data set for training and verifying the performance validation is still challenging for modeling the prototypes with robust perceiving capability. Various standard public benchmark datasets, along with their benchmark methods, are discussed in Table II. Additionally, the evaluated metrics such as Intersection over Union (IoU), Mean Average Precision (mAP), F1 score, etc, and their corresponding results are shown in Table III.

The following section discusses the details of multiple vision-based solutions with typical camera configurations for intelligent transportation. Further, advanced machine learning, deep

TABLE III
POPULAR BENCHMARK DATA-SETS AND SOTA - ADAS

Dataset	Annotations	Benchmarks	Method Name	Metric used	Results
Cityscapes [107]	5000 fine , 20000 coarse	Pixel-Level Semantic	HRNetV2 + OCR + SegFix	IoU	84.5%
Apollo [108]	146,997 frames , pixel-level pose information, depth maps.	Detection challenge	Megvii	mAP	48.43%
nuscenes [109]	1166187 annotations	Detection	Megvii	mAP	0.52
Lyft [110]	center_x center_y center_z, width length height yaw class_name	Lyft competition	Object detection	mAP	0.216
IDD [111]	46,588 total samples	AutoNUE Seg Object Detection	(MAIR) Faster R-CNN	mIoU mAP	*0.7579* ***44.6*** *%*
Kitti [112]	7481 train, 7518 test	Object Detection	PC-CNN-V2	mAP	81.43%
BDD [113]	100,000 images, 10 classes	Object detection	hybrid incremental net	mAP	45.7%
BIT [114]	9580 images, 6 classes	Vehicle identification	YOLO v2_vehicle	mAP	89.97%
AAU [115]	22 five-minute videos	Per-pixel, instance	-	-	-
Flir [116]	Recorded 30Hz, 10,228 frames	5 classes	MMTOD	mAP	61%
COnGRATS [117]	Sequences with COnGRATS surface normals, optical flow	—	—	—	—
Synthia [118]	Pixel-level semantic 200,000 images	Semantic Segmentation	MSFCN-2	mIoU	90.1%
LISA [119]	43,007 frames, 113,888 anno.	Detection	YOLO	AUC	58.3%
GSTRB [120]	50,000 images	Recognition	CNN - STN	Accuracy	99.71%
JAAD [121]	88K frames, 2793 unique pedestrians	Joint attention	SDS - RCNN	IoU	0.75
RoboCar [122]	20 million images	—	—	—	—
Trom [123]	400 GB size, 19 classes	Road markings	RPP	Pixel Accuracy	75.32%
Traffic Signs [124]	>20000 images, 3488 signs	Detect traffic signs	AFD	Mean precision	95%
Electra [125]	30Hz	indoor scenes	Multispectral piecewise	AMR	0.635
SHRP2 [126]	6,483,997 Trips	Driver Assesment	SCE expert-rater test	IR_Score	97%
UAH [127]	500 minutes , 3 categories	Naturalistic behavior	DriveSafe	—	—
Dronet CVL [128]	32,000 images, 137 seq	Drone Net	Resnet	F1 score	0.901
Toronto City [129]	712.5 km land, 8439 km road	Instance segmentation	Resnet	Mean	78.46%
Caltech [130]	10 hours of 640x480, 30 Hz video	Detection	Pedestron	RMR	1.76
FRIDA [131]	330 synthetic images, 6 scenes	Road scenes	NBPC + PA	Evaluation	31.9 ± 4.6
pothole [132]	300 images, ground truths	road surfaces	Fast AI + CNN	Accuracy	99%
INRIA [133]	614 train, 288 test	Object detection	PCN	LAMR	6.9%
AUC [134]	10 classes,12978 train, 4332 test	Classification	Kaggle competition	Multi loss	0.08
Waymo [135]	1,950 segments, 10 Hz, 4 classes	Object detection	YOLO V3 + Fusion	mAP	69.2%
Mapillary [136]	25000 images, 152 objects	Object Detection	—	mAP	46.8%

Acronyms and their details referring to Table III

1 Indian Driving Dataset (IDD)
2 Berkeley Driving Dataset (BDD)
3 Beijing Institute of Technology (BIT) Dataset.
4 Laboratory for Intelligence and Safe Automobiles (LISA) Traffic Sign Data
5 Joint Attention for Autonomous Driving (JAAD)
6 Strategic Highway Research Program (SHRP2) Naturalistic Driving Study
7 University of Alcala (UAH) Driveset
8 Intersection Over Union (IoU)
9 Mean Average Precision (mAP)
10 Mean IoU (mIoU)
11 Area under curve (AUC)
12 Active Metabolic Rate (AMR)
13 Resting Metabolic Rate (RMR
14 Log Average Miss Rate (LAMR)

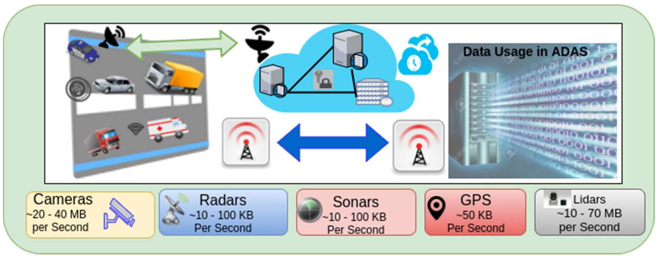

Fig. 3. Estimated amount of data usage in ADAS.

learning, and reinforcement learning algorithms and their applicability with ADAS are systematically reviewed along with the research gaps.

III. Vision Intelligence for Driver Assisted Systems

Autonomous vehicles need extensive computational resources to process the data feeds from cameras/sensors in real-time driving scenarios. It is anticipated that an ADAS system would produce a data rate of nearly (1 GB/sec). Nvidia provides a real-time information exchange among the GPUs with better frame rate. Additionally, the Nvidia DriveX platform provides state-of-the-art deep learning architectures, libraries, frameworks, and packages. These will further assist in validating the efficient deployment of algorithms for object location and mapping with lane identification.

A. Computational Requirements

1) *Greater Computing Power:* The driver-assisted vehicles would generate an enormous amount of data streams in real-time. For instance, L3/L4 levels of autonomy itself would approximately generate 4 TB of data in about 90 minutes of driving time [137], [138]. The estimated amount of streaming data from various sensors are shown in Fig. 3. Notably, there are a few recent works have been proposed on designing lightweight architectures for intelligent transportation. Borrego-Carazo *et al.* in [139], presented a systematic review on various GPU platforms such as Nvidia Jetson, etc. Dokwan *et al.* [140] proposed a lightweight end-to-end convolutional network architecture for real-time segmentation of high-resolution videos, NfS-SegNet, that can segment 2K-videos at 36.5 FPS with 24.3 GFLOPS. He *et al.* [141], proposed a novel facial landmark model and a lightweight architecture of Driver Status Monitoring (DSM) by integrating several deep learning models to monitor the driver's inattention. Kozlov *et al.* in [142] discussed various aspects towards the design and development of Real-Time ADAS Object Detector for Deployment on CPU. Wang *et al.* in [143], discussed FPGA-GPU and their implementations in heterogeneous approach for ADAS. Cao *et al.* in [144], proposed a modular feature fusion detector (MFFD) for road object detection. Hao *et al.* in [145] proposed a stylized design methodology with NAIS: Neural Architecture and Implementation Search for ADAS.

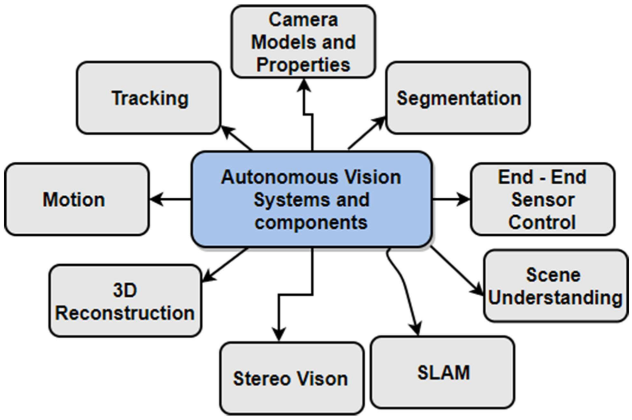

Fig. 4. Autonomous vision systems - integrated view.

2) *Security and Privacy:* In system-assisted vehicles, the data generated needs to be protected against technical threats. It remains essential that the information transmitted to and from inside the vehicle be protected for autonomous vehicles. There exist some recent works proposed on designing efficient frameworks to handle security and privacy issues in autonomous and assisted driving environments [146], [147].

B. Vision Mechanism for Smart Transportation

Computer vision (CV) encompasses methods, algorithms and techniques for acquiring, processing, and accurately understanding images. The integral aspects of different advanced computer vision systems, approaches, and techniques for ADAS development are illustrated as shown in Fig. 4. The primary tasks include: *picture identification*, *segmentation*, *3D reconstruction and monitoring*, *object identification*, *image classification*, etc. The geometric primitives of CV enable the detection and tracking of single object classes such as *faces, pedestrians, vehicles* in an uncontrolled environment for effective driver monitoring and assistance.

The use of image processing and computer vision techniques in analyzing a complex road traffic driving environment offers significant advancements over existing conventional monitoring methods. The following subsection discusses essential camera configurations, eye gaze, and head pose estimation for efficient system-assisted driving frameworks design.

1) Typical Camera Configurations: Autonomous vehicle assistance requires solutions that would address various vision challenges at different scales of abstraction. The vision-based system can facilitate with accurate location of the vehicle aligned with its environment. These could be further analyzed in following ways:

1) Analysis of pictures acquired over time.
2) Comparing and matching with n observations.
3) Adjusting a sequence of samples to the model.

This subsection discusses different camera models, eye gaze and head pose estimation methods, and SLAM techniques towards autonomous driving and navigation.

Fig. 5. Illustration of FIR and NIR image samples.

1) *Monocular Camera:* Monocular camera is a progressive camera that is used for monitoring scene descriptions. Notably, it can be deployed with limited size and low cost. The main limitation is that the objects to be recognized are limited in size. Typically used for lane recognition with lane assistance, warning driver with traffic signs [148] such as speed limit and obstacle detections.
2) *Stereo vision Camera:* The 3D recognition of vehicles is highly essential in autonomous driving. In particular, this requires in-depth information collected using stereo cameras like depth mapping. The stereo cameras can depict the depth information more precisely [149], [150]. Eventually, for distance calculation, a triangulation method is used to convert the disparity map to a distance from the geometric arrangement of the camera.
3) *Dash Cam:* Dash camera gains optical details about the vehicle in external road environment. Moreover, it has constraints over different visual cues of the perceived scenes. Notably, there have been some works using Dash Cam based analysis such as anomaly detection [151], predicting the traffic accidents [152] etc.
4) *Kinect Camera:* The depth details from Kinect cameras are fused to verify the spatio-temporal motion displacements to project on the screen: an RGB channeled VGA camera, a depth sensor, and a multi-array microphone. Kinectv2 sensors are widely used for applications such as face tracking, mapping, or cyclic deformation assessment.
5) *FIR camera:* The modern night vision system uses a thermal imaging camera to improve the visual scene perception in dark or snow/fog weather beyond the vehicle headlamps. The visual instances of both FIR and NIR cameras are shown in Fig. 5.

Modeling of facial keypoint extraction, head pose, and gaze estimation is obtained using open source framework Openface2 [153] and is shown in Fig. 6. Typically, these key/interesting points are significant to determining any driver

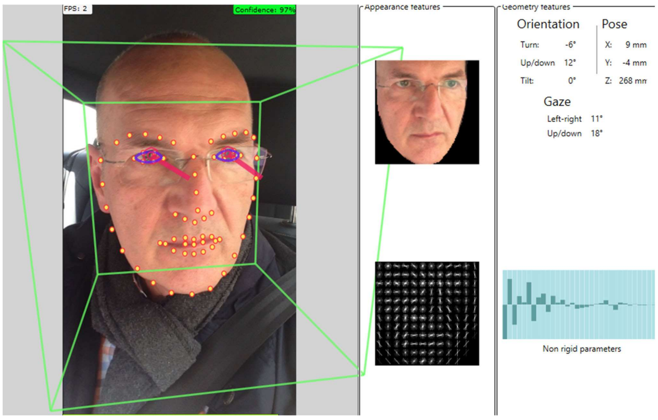

Fig. 6. Result of gaze estimation for driver in-vehicle.

face's geometric and topological structure. The head poses estimate gains with 3D orientation for a turn, up/down, and tilt. The gaze examines the geometric features of eye movements combining left/right and up/down.

2) Eye Gaze Estimation: The coarse/fine gaze trajectory and the driver's head are functionally acceptable in vision-based driver behavior pattern-monitoring systems. Recently, several monitoring systems have been investigated to analyze driver attention status in real-time. Since the head pose pertains to the direction of the gaze, several advanced procedures for estimation of the gaze zone considering the head orientation as an indicator were proposed. Notably, effective gaze estimation results from the integration of head pose and gaze estimation (Angle value of eye) [154]. The standard eye-tracking tool used is Tobii eye-tracking mechanism [155]. For gaze estimation, Zhang *et al.* [156] proposed a new MPIIGaze dataset that contains 213,659 images. Fischer *et al.* [157] discussed how to evaluate head position using a motion seizure model and eye gaze from eye-tracking glasses and proposed a unique real-time method on geometric visual primitives based deep CNN with improved functioning to handle diversified images. Similarly, Kyle *et al.* [158] in their work presented on Gaze Capture, the first wide-scale data records for eye tracing, containing records of 1450 participants, comprised 2.5 million frames. Cristina *et al.* [159] recommended combine facial, eye pupil movements, and 3D face keypoints as individual streams in CNN to predict gaze patterns in a spatial frame. This paper showed a significant improvement of 14.6% over the EYEDIAP dataset.

3) Head Pose Estimation: Recognizing driver's perception is a significant precondition for the implementation of advanced automotive safety features. Even though visual attention is limited to the driver's drivability range, realizing accurate driver focus provides clues regarding drivers' activity. In addition, proper head poses analysis of the driver would benefit the recommendation system from predicting any dynamic behavior patterns in the vehicle. The authors in [160], recommended a methodology for learning a head-position model with five key-point locations. Further, the authors discussed a CNN-based framework focusing on the probability distribution of key points with the heat-map images. The model was evaluated and the performance was compared for BIWI and AFLW datasets. Ruiz [161] proposed a new technique for determining pose training with the 300W-LP multi-loss convolution network. Further, it was used to anticipate the inner Euler angles (yaw, pitch, and roll) specifically from the image intensities. Tsun [162] proposed a new technique with fine-grained aggregation for verifying the in-vehicle positions of the driver's head from a single image. On the other hand, Shao *et al.* [163] discussed new methods for adjusting the bounding box coordinates and optimizing loss function.

4) SLAM and Localization: A vehicle transition in rigorous diverse road conditions with encircling obstacles and recognition of other road entities requires a precise location framework for safer driving suggestions. Simultaneous Localization and Mapping (SLAM) is one of the methods used for localization. SLAM helps to create a model within dynamic driving environments. SLAM solutions require an array of algorithms to ensure the reliability of the location. Ros *et al.* [164] discussed various visual SLAM methods in the scope of urban ground vehicles. It also examined optimization methods for urban navigation. Bresson *et al.* [165] compared and reviewed various existing SLAM methods such as filter-based, optimization-based, and graph-based SLAM mechanisms. Notably, a few challenges, such as eliminating or reducing the risk of drift, were addressed. Zhao *et al.* [166] proposed a novel General SLAM framework (GSLAM), that not only provides evaluation capabilities but also assists a useful toolkit for researchers to develop their custom SLAM systems rapidly. Bloesch *et al.* [167] presented a novel dense geometric representation of the external driving scene, conditioned on the frequency data of a single image and obtained with a few parameters. Seong *et al.* [168] suggested methods based on loose bonding of direct & feature-based methodologies such as:

1) The local direct method is to monitor the camera position and orientation quickly with internal accurate, short-term, dense mapping.
2) A global artifact based approach to fine tune key frame poses.

SLAM works in two-stage approach - *Localization* (understand the position of the map) and *Mapping* (understand the map, given its positions). SLAM modeling is used for mapping, sensing and kinematics for complete real-time environmental perception. Despite notable benefits of SLAM for reliable localization with mapping using various filters, there is a data association problem that limits the scope of its use to a certain extent. The data association problem [169] arises when landmarks cannot be uniquely identified, causing the number of possible hypotheses to grow exponentially, rendering the SLAM for large areas completely nonviable. Data association in SLAM can be summarised as a feature correspondence problem where two features observed at separate locations and times are identified as belonging to the same physical object in the world. Further improvements have been in progress with the use of vision and 2D information. A challenging research problem that needs to be addressed is integrating the SLAM with multiple filters and tracking to increase robustness. The next section discusses in detail different machine intelligence algorithms and their adaptability for ADAS.

IV. Computational Intelligence for ADAS

Machine intelligence is a powerful subset of artificial intelligence that could help address various real-time challenges towards autonomous/system-assisted driving. The various applications involve categorizing the driving scenario or monitor driver state analysis with fusion data from multiple sensors. It is a complex and nontrivial task to develop ADAS with L4/L5 levels of autonomy. Over the period, significant proposals have been made to address the diversified challenges. Typically, this includes precise object localization, semantic and instance segmentation with convolutional neural networks. The machine learning techniques can handle the information from the continuous rendering of the driving environment with dynamic changes. Further, this analysis could be categorized into four subtasks:

1) Object detection.
2) Object identification or recognition.
3) Object localization.
4) Movement prediction.

The following subsection discusses different learning approaches while modeling a network, such as supervised, unsupervised, reinforcement, and deep learning.

A. Supervised Learning for ADAS

Supervised algorithms learn better through training dataset and accelerates learning rate till the desired level of confidence (least probability error) is observed. It involves classification, regression, dimension reduction or anomaly detection.

1) *Pattern Recognition:* In ADAS, images streaming from sensors have diverse data with all environmental factors. Filtering of such images is required to verify for samples belonging to that category and removing the noise information from data points [170]. The features of an image (geometric primitives) are combined to determine an object. Most common methods include Principle Component Analysis (PCA), Histograms of Oriented Gradients (HOG), Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Bayesian, etc. Further, it helps in classification tasks with rule-based inferences.
2) *SVM:* SVM uses hyperplane that could define decision boundaries. Bougharriou *et al.* [171] proposed HOG and linear SVM for the classification of the vehicle to detect obstacles in the driving environments. Navarro *et al.* [172] compares various machine learning algorithms along with KNN, Naive Bayesian, and SVM for efficient pedestrian identification. Xing *et al.* [173] proposed a feed forward network to differentiate normal and distracting driving tasks.
3) *Regression Algorithms:* The main use of regression analysis is to predict the events. Regression analysis estimates the relationship between two or more variables with:
   1) Total number of non-depending variables.
   2) Type of depending elements.
   3) Geometric shape of the observed regression line.

   In ADAS, images (RADAR or Camera) are fundamental requirements for object localization. However, the challenge is to develop an efficient model for prediction with an optimal preference for image feature embedding. Hyodo *et al.* [174] discussed the impact of constant naturalistic driving sequences on driving behavior in the vehicle. The piece-wise regression model was used to find the relation between driver condition indices (continuous hours) and driver behavior indices (velocity deceleration and deceleration distance). Ali *et al.* [175] presented the relation among the weather conditions and driving lane reliability using the naturalistic driving data.

4) *Decision Matrix Algorithms:* Decision trees are used to systematically identify, analyze, and measure relationships between sets of values and data. Some of the standard techniques include decision trees, Gradient Boosting Machine(GBM), and AdaBoosting. The authors in [176] developed a support system for compulsory lane deviations on roads with broken white lanes, using a mixture of learning algorithms such as decision-tree and Bayes.

5) *Ada-Boost:* This algorithm is a fusion of multiple learning algorithms for regression or classification tasks. Geronimo [177] proposed a hybrid flow of various Haar-based cleansing techniques and Edge Orientation Histograms (EOH) to analyze pedestrian detection models. Ada-Boost has strong prediction and potential to cascade architectural features enhancing the computational throughput.

The following subsection provides a detailed view of the application of unsupervised learning with clustering approaches for system-assisted driving scenarios.

B. Unsupervised Learning for ADAS

Unsupervised learning models the relationship from a data set to find patterns or cluster data into subgroups as per similarity information. Unsupervised algorithms can be classified mainly as clustering techniques.

Clustering: In images captured from the real world, it is not easy to detect/locate objects. The most widely used methods are K-means and multi-class neural networks. Yiding *et al.* [178] analyzed the pros and cons considering three different clustering methods (Gustafson Kessel approach (GK), Fuzzy based C-Means (FCM), and Gath-Geva (GG) technique) in the direction of drivers steering intention. Wenshuo *et al.* [179] focused on clustering a broad aspect of driving scenarios depending on multi-vehicle GPS trajectories. Friedrich Kruber *et al.* [180], proposed a modified random forest algorithm with a proximity matrix approach for Automatic Traffic Scenario Categorization. Rachael Abbott *et al.* [181], proposed a novel unsupervised adaptation to the cycleGAN architecture to translate the non-corresponding LWIR/RGB datasets. Yongquan Xie *et al.* [182], proposed and developed Adversarial Discriminative Neural Network for Multi-Temporal Signals (MTS-ADNN) architecture for driver workload learning through time-stamped signals. S. Zhou *et al.* [183], proposed a novel generative feature learning framework with inductive clustering bias for few-shot learning-based recognition of traffic signs.

C. Reinforcement Learning (RL) for ADAS

The goal is to find an optimal behavior by iteratively exploring the environment. The agent realizes to act in the environment

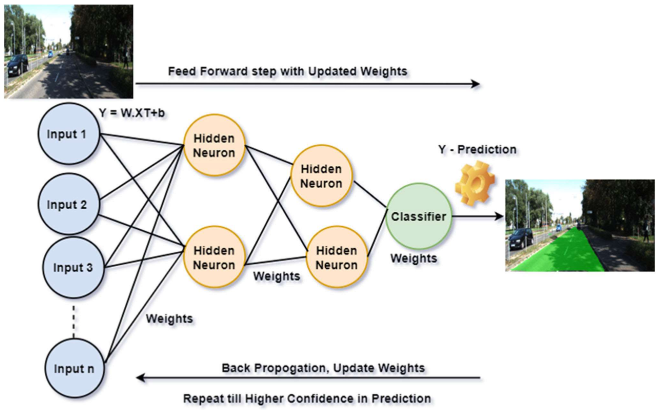

Fig. 7. Neural networks functioning - ADAS.

based on rewards. The authors in [184] highlight the decision system for diversified road traffic conditions and associated design problems. Wang *et al.* [185] proposed a Q-function with optimized learning of agent (vehicle) and model semi-automated manner of lane deviations. Chen *et al.* [186] proposed a framework that could enable optimized deep reinforcement learning for challenging scenarios. Zhiyuan Zhao *et al.* [187], proposed reinforcement learning with lane identification models for precise lane detection and localization using the Q-learning localizer approach. Khaled *et al.* [188], presented an Inverse Reinforcement Learning (IRL) and the bidirectional recurrent neural network architecture (B-LSTM) approach for pedestrian's trajectory prediction. Kiran *et al.* [189], presented a systematic review of various reinforcement learning algorithms, their challenges and compared driving simulators. Ure *et al.* [190], proposed an automated approach using the Model Predictive Control (MPC) weight tuning process, trained the agents in the simulation. The primary idea behind reinforcement learning (RL) is to use the identified states and rewards obtained from the environment to regulate an agent or a process while interacting. Decision making and control [191]–[193] is a critical and complex task for applications such as lane change maneuver control, vehicular control, etc. However, the reliability in vehicular control through decision-making is a research gap that is yet to be addressed.

The following subsection discusses various aspects of deep learning involved in modeling effective state-of-the-art object detection mechanisms. Further, it also demonstrates the practical implementation of deep learning algorithms with significant results for heterogeneous real-time traffic environments.

D. Deep Learning

The motivation of deep learning is to simulate the human brain to establish a neural network, which can interpret multi-modal data. The typical working functionality of a neural network is shown in Fig. 7. When passed through regular neural networks, spatial information will not retain any of its local spatial connectivity. Further, this will result in insufficient, missing low/high-frequency information. Convolutional deep neural networks with mathematical perspectives in formulating models are used to address the above research gaps. Significantly, in recent

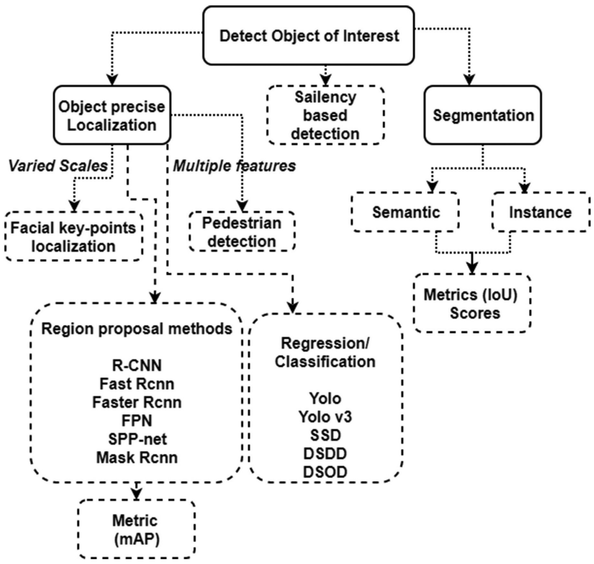

Fig. 8. Generic Object detection framework categorization.

times models like Auto Encoder, Restricted Boltzmann Machine (RBM), Deep Belief Network (DBN), Convolutional Neural Network (CNN) [194], Deep Neural Network (DNN), Recurrent Neural Network (RNN) [195] have gained importance. A few deep learning applications include image classification, face recognition, object detection, pedestrian detection, and video analysis.

1) Modelling Object Detection Using Deeper Architectures: Object detection focuses on how precise the objects are located in scene descriptions, with semantic understanding of images and videos. Despite the existing conventional mechanisms for feature extraction such as Haar Cascades, Scale Invariant Feature Transform (SIFT), HOG, and Adaboost, it cannot still extract core features. However, various vision-based challenges such as *illumination, resolution, viewpoint variance, scaling effect, rotation in-variance* factors still need to be addressed. An image detection framework categorization is shown in Fig. 8. Object detectors were divided into two stages: A two-stage region-based frameworks such as feature hierarchies for object localization [196], Faster R-CNN [197], region-based detection [198], feature pyramid approach for detecting objects [199] use region proposed network (RPN). A single-stage frameworks such as YOLO [200], SSD [201], [202] were proposed for addressing shift between speed and accuracy with optimized computations.

The scope of the object detection task with enhancements has been progressed significantly in recent years. CornerNet [203], a new paradigm was proposed, where object coordinates are detected as a pair of key points using a single convolution neural network. Notably, this approach reduced the need for a set of anchor boxes. A modified two-staged Faster R-CNN approach was used to analyze the road traffic in unconstrained environments with density estimation [204]. DetNet [205], was proposed as backbone network for object detection. Subsequently, DetNet offers additional steps for picture classification, maintaining higher spatial resolution for deeper layers. Instance segmentation tasks on the MSCOCO dataset were evaluated on DetNet (4.8 G FLOP). Libra R-CNN [206], an effective framework was developed for structured and balanced object detection. Further, it is modeled by a mixture of three components: *IoU-scaled sampling, distributed image pyramid* and *Absolute error differences computing L1 loss*. A ScratchDet [207] was proposed, which integrates the BatchNorm to help the detection model converge from the initial phase irrespective of the network. Later, stereo Region Proposal Network (RPN) [208] was developed for predicting the sparse interesting values, view angles, and traffic entity measurements to compute a coarse grain 3D obstacle from coordinates. Several efficient architectures were proposed in recent times, such as ShuffleNet, and MobileNetV2. However, all these models depend on depth-wise separable arrangement of convolutions which lacks the optimized development approach currently seen in most deep learning frameworks. A new architecture PeleeNet [209] was proposed, primarily modeled with convolution operation. PeleeNet is optimized as 66% of the overall model size of MobileNet. Such lightweight models were considered for real-time deployments.

DetNAS [210] mainly focused on pre-training the one-shot supernet technique on ImageNet and further fine-tune the neural architecture search using an evolutionary algorithm (EA). Lightweight RetinaNet [211] was proposed to minimize the largest bottleneck layer for the lightweight RetinaNet mAP-FLOPs trade-off. Empirically, the proposed method scores 0.1% mAP with enhancement at 1.15 x FLOPs and decrease with 0.1% mAP progress at 1.15 x FLOPs and 0.3% mAP enhancement observed with 1.8 x FLOPs reduction. Centernet [212] model was proposed with a low cost of visual patterns inside each cropped area. Here, an object is identified using triplets instead of key points, providing enhanced accuracy and recall. A novel Trident Network (TridentNet) [213] was proposed intended to produce a scaled feature map in a uniform arrangement. TridentNet works based on the weight-divided trident blocks and is further modeled to achieve scale-aware training scheme.

One interesting problem to focus on would be detecting a completely unseen and new obstacle given the vast diversity in obstacles. Many works have been in progress to address the annotation challenges and use fewer training samples with one-shot [214], zero-shot [215], and few-shot [216] learning approaches. Despite such few-shot learning, the overfitting and multi-dimensional parameter level issues still need to be investigated. Subsequently, continual [217] and attention [218] based object detection approaches was proposed. However, these systems could generalize/ localize the obstacle only seen in training samples. Nevertheless, it still could not identify new objects and remains a contemporary challenge. Significantly, with the latest proposed architectures such as vision transformers [219], incremental learning [220], the problem of detecting unseen objects can be investigated by designing a multi-headed [221] architecture. Vehicular behavioral prediction and next move assistance is equally important in autonomous driving, particularly for lane keep assist etc and/or platooning applications. Typically, this requires multi-sensors like RADAR, LIDAR, IR and/or Camera fusion data with advanced tracking techniques [222], [223] to understand the neighborhood vehicles for next step prediction. Notably, the state estimation of other vehicles is required to anticipate the probabilistic next move especially for achieving L3/L4 levels of autonomous driving in less-disciplined chaotic traffic environments.

V. Conclusion & Future Work

An efficient development and deployment of advanced driver assistance systems (ADAS) with a diligent L4/L5 level of autonomy would provide a safe, comfortable and autonomous driving experience. However, it is exceptionally challenging to develop a completely autonomous driving system in places with less lane-disciplined traffic. In this regard, this paper presents a detailed, systematic, and progressive review of different sensing mechanisms, important ADAS features that would support L2/L3/L4 levels of autonomy. Various multi-sensor systems used in ADAS were examined in detail, along with their limitations in real-time. Additionally, as a next step, the benefits of fusing various vision, IMU, IR, LIDAR, RADAR sensors are verified and presented. Further, this work highlights the different research gaps and the possible future directions for the ADAS features. Subsequently, this work provides details of various standard datasets and describes vision and machine intelligence techniques and algorithms for efficient design and implementation of advanced systems. Notably, the machine vision and advanced deep learning techniques for analyzing the head-pose patterns, eye gaze estimates, and SLAM approaches for different applications in intelligent transportation are discussed. To summarize, this paper presents multiple research gaps in ADAS features, highlights the need for multi-sensor fusion, discussed technological advancements to address the potential gaps. Significantly, this work would be a road map for researchers designing L3/L4 capability levels for driving/self-driving vehicles that would help complete visual perception and passive driver assistance in a heterogeneous road traffic environment.

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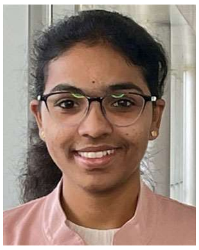

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