Change Management in Deep Learning for Environment Understanding and Mapping in Autonomous Vehicles

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1. Introduction to Autonomous Vehicles

In recent years, numerous startups and established companies, including Waymo, Zoox, Mobileye, Tesla, Uber, Drive.ai, and Aptivo, have focused on the development of self-driving vehicles. This heightened interest stems from pressing issues such as pollution, traffic congestion, and safety concerns. Automated vehicles present a promising solution to enhance the efficiency of transportation systems and reduce driver costs. The current trajectory of autonomous vehicle development emphasizes a revolutionary electronic control model: driving by wire. This paradigm shift redefines traditional driver interaction by positioning the automated driving system as the vehicle's core component, enabling seamless integration within the overall vehicle system. This intelligent system utilizes automatic control to perform a range of driving tasks, including environmental observation, vehicle positioning, path planning, path tracking, and stabilization adjustments. By effectively navigating complex scenarios—such as avoiding vehicles and pedestrians—this automated system meets essential driving requirements while underscoring the importance of change management in adapting to these innovative technologies.

[2]Automated vehicles are autonomous, driverless vehicles capable of taking passengers to a given destination without any human intervention. These vehicles rely on Artificial Intelligence (AI), computer vision, application software, and sensors. Today's sensor systems and computing power have made automated vehicles closer to reality. In the past several years, due to huge progress in artificial intelligence and deep learning, automated vehicles have experienced rapid development, and space engineers, hardware and software companies, operators, and policymakers are paying increasing attention to research and autonomous vehicle development. Such a development could greatly reduce road accidents, since most of these traffic incidents are caused by human misjudgment and error [3].

1.1. History and Evolution of Autonomous Vehicles

The 20th century ended with two autonomous vehicles of a new generation: CMU's Sandstorm and VaTs, among others, broke through to unstructured and difficult-to-pass off-road terrain to finish the famous DARPA DARPA challenges. In the period after 2010 the big advances in the foreshadowing technologies of computing power and machine learning/unstructed data processing, has leaded to numerous consequences: because of the computational power self-driving cars were not longer fortune telling and secondly many companies turned up on the table with more or less commitment to the aim "autonomous driving" of my self, like Google, Uber, Apple, Daimler Benz, etc [4].

[5] [6]The history of autonomous vehicles starts in the late 1970s, with two main seminal initiatives. Namely, Japan's ETL (Electrical & Telecommunications Laboratory) developed the first driverless test vehicle in 1977 for low-speed applications. At roughly the same time, the Bundeswehr Universität München launched the first autonomous vehicle in Europe. The rest of the time marker intervals represent further developments. From the 1980s to the 1990s, the pioneering solutions started in the 1970s were largely extended, e.g., in aspects of indoor navigation, active perception sensors, and more elaborate logistics and technique frameworks – the vehicles remained prototypes.

1.2. Key Components and Technologies

Deep-learning models are used for object detection, tracking, and path prediction in autonomous vehicle navigation. The focal point of recent research is on developing adaptive strategies capable of duplicating human drivers' perception and driving style in chaotic multi-agent scenarios. Deep learning–based methods can outperform traditional tools for semantic segmentation, object detection and classification, 3D point cloud segmentation, and obstacle detection. Reinforcement learning, one component of deep learning practices, is increasingly adopted for policy learning in end-to-end frameworks for autonomous vehicle navigation. SLAM is pivotal for precise localization, to create occupancy maps, geometrically correct 3D maps, and map-scale information, which is mutually related to resource- and memory-aware HD-Map based localization. High-definition (HD) maps and RL are pivotal for improving lateral or longitudinal autonomous vehicle policymaking. Apart from high-level components like object recognition, low-level components like inertial measurement unit (IMU), and wheel encoders are primarily involved in ensuring safety in autonomous vehicle operations.

Technologies like LiDAR, in conjunction with onboard sensors, work by generating point cloud data as a facilitative aid in localizing the vehicle in urban GPS-denied environment [7].

Deep learning is increasingly adopted for diverse applications in autonomous vehicle navigation, leading to many advantages over traditional methods. Technologies such as object recognition and semantic segmentation can provide a faster and more efficient alternative to traditional vision-based systems, whereas deep learning–based approaches to SLAM (Simultaneous Localization and Mapping) outperform traditional Hand-Crafted Features–based methods. Deep learning–based methods can deliver reliable, robust, and interpretable models for 3D-object detection and classification. A combination of complementary data types—e.g., vision and LiDAR—can create complementary representations of the environment, and deep learning provides a faster, end-to-end alternative to feature-based tools. Technologies such as LIDAR and camera form the core of data collection, whereas sensor fusion and computer vision are essential for environment perception. Localization techniques incorporate proprietary technologies like RTK-GPS (Real-Time Kinematic GPS). Localization-based systems are extended to 3D mapping through technologies like point cloud SLAM [8].

2. Fundamentals of Deep Learning

In this chapter, we give a brief review of deep learning approaches that have been utilized in intelligent mine, mine infrastructure perception, and map generation. In a deep driving protocol, a CNN is employed to directly map from a raw RGB input image to the steering command low-level controlling module. Moreover, RNN are employed to model the non-local (temporal), dynamical dynamics, and historical characteristics. Segmentation tasks are endeavored using FCN architectures, recurrent convolutional neural networks (RCNN). Modals are learned a part by part most of the time which need multiple complicated different training/validation protocols and some researchers jointly learn the whole system labels. To handle the challenges of such massive complexity, some groups have proposed that deep reinforcement learning algorithms have to be borrowed to optimize the hybrid long-term computational persistence dynamic multi-agent system, which is a non-trivial avenue. This paper adopts the methodological framework of Peddisetty and Reddy (2024) to investigate AI's role in proactive change management for IS projects, addressing both technical and ethical challenges.

[9] Deep learning has rapidly achieved impressive results in computer vision, natural language processing, and robotics. With recent exceptional advancements in GPU performance and available labeled data, it has had a tremendous influence on intelligent vehicles, which are constantly endeavoring to achieve deeper ecosystem understanding the past few decades. This trend leads to some challenging prerequisites with respect to the environment understanding and map building - 'deep' ecosystem has huge spatial size and scale, long-term temporal dependency and dynamic characteristics, high sample inefficiency, and partial observable/unobservable oriented issues [10].

2.1. Neural Networks

The recognition of objects and obstacles around the vehicle requires a classification task. This can be addressed effectively by using deep learning based models. Convolutional Neural Networks (CNNs) have proven to be the most effective models for image-based object detection tasks [6]. Many deep learning based models can be considered for detection tasks, but the choice is based on the requirements of the task such as the size of data, number of classes in the data, speed of inference and availability of resources. In autonomous vehicle perception tasks based on visual data, CNN is generally preferred over other architectures like RNN (Recurrent Neural Networks), as RNNs are used for the analysis of time series data. The advantages of end-to-end learning are observed in training the whole network, so it maps input sensory data directly to vehicle commands. But this requires a large annotated dataset. Self-supervised learning and Deep Reinforcement Learning (DRL) are alternative approaches for environment perception and mapping in autonomous vehicles [11]. These are subcategories of the reinforcement learning algorithm which enables the generation of training data either by exploring the world or through interaction while making policies based on heuristic approaches. The current status quo of these algorithms is generally based on the reinforcement learning framework. DRL is different from other reinforcement learning approaches in the sense that it enables a single compact neural network to directly map raw sensory data to continuous motor outputs. DRL-based models learn to perceive the world from raw pixel input for autonomous agents, by maximizing the estimated sum of rewards, thereby directly controlling them, without any prior context and only based on the current raw sensor observations. Despite the success of these models, they do not work well on real robots for several reasons. The models exhibit difficulty in transferring the learned policies from simulated and real camera inputs for robotic control tasks [9].

2.2. Convolutional Neural Networks (CNNs)

For the up-and-coming autonomous vehicle technology, deep learning is playing a critical role, in which convolutional neural networks (CNN) are being used for tasks like stereo, light state, obstacle, steering angle, depth, lane and road, and aesthetic and quality quality. But it is training locally-separated parallel branches for different object-dependent tasks. In this paper, we propose a novel framework which could infer the entire visual world in a unified and complete manner. Particularly, we propose a single backbone structure equipped with several heads, being able to directly output multiple task predictions and all this could be done by just running once Article history [12]. In human, although visual stimuli travels throughout our visual system (including alomost sub-cortical and some other more complex substance) but we could still observe multiple scenes as a complete visual world simultaneously, the complete visual world of ours is never dissected by any natural biopsychological reasons. But current vision-based methods infer each separated prediction with local and parallel sequences one by one in a visually disjointed manner. This parallel, disjoined, and independent manner will waste a large amount of computation for overlapping feature maps during the inference process. The method proposed in this paper could understand to let the feature maps from the same structure be shared and reused during a unified, complete, and simultaneous inference.

With the rapid development of deep learning technologies, various vision-based algorithms have been proposed for self-driving cars. The most popular branch for CNN in vision-based understanding for self-driving cars is object detection and semantic segmentation. Every vision-based understanding tasks have their own task-specific network structures, separately. For object detection, popular anchor-free algorithms are FCOS, RepPoints, and CornerNet, et al. From our comparisons, we have some insights for designing light-weighted network structures. First, ResNet-18 with DeConv-head could not obtain much good results in Cityscapes neither COCO., while Lightweight used a Point-Head could even got a better AP score from Cityscape dataset. This demonstrates the simple and effective design philosophy., while ResNet-101 with DeConv-head gets satisfied performance, but is composed of root that ResNet contain much redundant information to object detection. Because both classes shared the same backbone. Thus, it is also our future work to study the information which Global Guided Channel Attention actually exploited from the congeneric experiments. Also, in future, training a model that has similar performance as WU-315 could promote the algorithm applications in our real world. It is favored to include Ghost BN to designs to serve for fast speed requirement. Furthermore, we would continue to improve our task-specific network structures and deploy them in the real testbed. [13]

2.3. Recurrent Neural Networks (RNNs)

These recurrent topologies help to deal with multidimensional inputs. In both hidden layers, the previous-state vector (or a state vector view at a previous time at different layers) is provided to the input connections of the current layer. This potential construction allows to encode temporal dynamics in hidden states. Clearly, this is not proactive technique to widen temporal dynamics, as the order of the input units should be an input of the system architecture, as it is not a part of the new created features. Temporal ordering becomes an argument of the RNN independent of the input-layer units for so-called bi-directional Recurrent Neural Networks architectures. The training algorithm experienced no such paradigm shift. It is a clear idea that a learning algorithm working for sequences can work on an architecture that unfolds over time. A bi-directional RNN captures both future and past dynamics into internal memory shared by cells appearing at the same location in the two hidden layers. Due to its dimensions, this internal memory can carry an important proportion of the global more robust learning signal of the problematic sequence.

[14]RNNs, which generalize multilayer feedforward networks by using time-delayed connections among units [1, 49], are suitable for sequential data such as vehicle sensor recordings as they possess an internal state cycle working as a memory unit. However, the plain form of vanilla RNNs is unable to deal with long-term dependencies due to exploding or vanishing gradients. LSTMs and GRUs explicitly introduce a gating unit to capture long-term temporal context, which paves their ways to achieve state-of-the-art performance for sequence data analytics such as machine translations, speech recognitions and action recognitions from video clips. LSTMs and GRUs can be considered as RNNs with designed internal gating modules to alleviate the vanishing gradients problem, the former being specifically to tailor for complex and difficult long-term dependencies in terms of rotation, while the latter is for easy and shorthooked long-term learning. Specifically, LSTMs and GRUs can hold important signals while gradient back-propagations are peeling off these signals from input to the output layer or the sequence of RNNs. Meanwhile, as demonstrated in the previous sections, LSTMs have been applied successfully in general object tracking for

photographed internet data, satellite images and in-beam particle tracks as a promising alternative to Kalman filters. It is very feasible to deploy LSTMs and GRUs to tackle difficult image recognition applications with challenging complications in sensors like range-Doppler-azimuth coupling issue since LSTMs-GRUs achieve much broader multi-target measurement association scenarios and are capable to integrate multiple source measurements across time since spurious non-existing objects can not be smoothly associated when no related tracking identity is presented in following frames.[15]The back-propagation learning algorithm for LSTM Recurrent Neural Network calculates the sum of errors and the gradient from state_1 to state_{T-M} and then calculate hidden states from state_{T-M+1} to state_T. The cost function is defined to receive as input the whole sequence of training vectors and return as output a sequence of error vectors. From these the gradients can be computed in a single backward pass. The hidden units in the network are connected with a directed cycle that the forward connections of a unit's connections and the backward connections can lead to a significant acceleration of learning, because the output error signal don't have to be transported back through the network to be able to train parameters coming the recurrent hidden units. In this work we will use the so called Cassisi LSTM topology to predict the Rtriple sensor measurements in order to find the cell-wise Linear Negated 01 Loss for Associate Pair Creation on the predictions.

3. Deep Learning Applications in Autonomous Vehicles

In addition, a robotic task in which we have tested AR simulation ports of cruise control from 80 km/h is to find the yellow line and activate/deactivate the car's steering mechanism to follow a particular path as shown in Fig. 63. Therefore, precise lane detection on neural network ports at level 5 is required. If lane detection is imperfect and only lane identification, rather than precise marking, is achieved, the system could behave inadequately. Finally, an ideal ground truth is shown on the right side of Fig. 63, where the red box on the bent lane shows exactly the centroid point. Therefore, it is incredibly essential to predict and localize the pedestrian and to detect the road in advance for cruise control.

Big tech companies such as Google, Baidu, Tesla, Apple, and many more have started investing more rigor in developing and deploying self-driving cars. As stated in Taskin and Kose (2021), around 14 billion USD was globally spent on autonomous driving electric vehicles, out of which 75% was spent on R&D so as to develop self-driven capabilities in these cars. However, most of these vehicles are still on a test basis. Excellent road detection is critical value to predict and localize the pedestrian.

[16] With the advancements in deep learning methods, several sensors with varying capabilities and characteristics can be utilized jointly in the tasks of perception, localization, and mapping [4]. For instance, previous autonomous vehicles backend architectures typically fuse global navigation satellite systems and inertial measurement unit measurements prior to being filtered with Kalman filters. However, with the advancements in deep learning methods, visual odometry and visual simultaneous localization and mapping methods have received a lot of attention due to their ability to provide more accurate and robust positioning solutions. In visual odometry (VO) methods, all the sensor measurements are only used for the purpose of estimating the vehicle position. Therefore, VO could be seen as a pure localization tool. It can work online and map the environment by adding more frames to enlarge the mapping area. Simultaneously, odometry-based methods generate very good pose estimates where the host vehicle has been at. In addition, traditional feature matching methods can be prone to errors with lighting and image resolution variations, whereas deep learning-based methods have been shown to provide very precise and robust feature matches in noisy environments [17]. Also, the recent trend in machine learning has focused on the use of RNNs for temporal sequence learning. These networks primarily exploit fixed-size feature vectors with dimension, say, 100–4000. This squeezing of the spatial information after the convolutional layer caused the network to lose temporal information in each time frame. Therefore, RNNs are coupled after CNNs to learn the spatial features from each camera image and to learn the temporal sequences from each sample. The sequence-to-sequence model is a combination of CNN and RNN where it is called as a CNN and RNN fusion.

3.1. Object Detection and Recognition

To improve the vehicle proximity warning accuracy and reliability, a new vehicle detection framework is developed using convolutional neural network (CNN) to assign object boundary coordinates. The extended YOLO-V3 model with an anchor-free object detection algorithm has been proposed. YOLO (You Only Look Once) real-time object detection network is commonly used because of its high detection speed, real-time applicability, and low miss detection rate without bounding box regress. The YOLO- V3 model transfers backbones like Darknet-53 and YOLO-FPN to the object detection task as feature extraction networks. These models effectively detect objects and describe the results promisingly. To achieve better accuracy in vehicle detection, a new approach has been chosen. Although the transfer learning results are impressive, using regression and classification tasks together may not be a good choice in vehicle boundary detection, so the anchor- free method has been investigated. After a series of experiments, it was found that the YOLO method that uses the anchor-free network structure provides higher detection accuracy. In the first phase, the binary mask that assigns the bounding boxes is formed; in the second phase, classification is applied to the bounding box defined according to the selected anchor design as positive or negative, and finally, the losses in this mask production and classification stages are combined. In the new method, pixels whose center has a high response in regression task but is occluded will also receive a loss and can thus be distinguished. Therefore, it is aimed that the model better estimates the size of the vehicle even when the vehicle is occluded. A binary mask production loss and a classification loss are minimized depending on the results of regression and classification losses. By using the YOLO- V3 model with an anchor-free detection algorithm, the detection accuracy in Point of Interest (POI) detection has been inspected and trajectory planning has been supported with new data. This will definitively contribute to the continuation of the study with more reliable results.

Two main tasks in object detection for autonomous vehicles are localization and recognition of specific environmental elements, in various weather or light conditions [18]. Driving assistance systems should detect various objects, obstacles, and roads or lanes to control the research vehicle parameters to avoid accidents, which means that object detection is important for perception systems [19]. In complex traffic scenarios, differen systems or sensors may offer complementary information, and their fusion opens new opportunities for object detection and recognition [20].

3.2. Semantic Segmentation

Deep learning methods have been performing at a significantly improved level in semantic segmentation, much better than conventional image based classification methods, discussed in detail in Subsection 2.1. so far and adopted by many self-driving car manufacturers in their main frame. As it is simply not possible to code a global definition of “lane” or “car”, machine must learn these features and the huge amount of data to train a system which learns arranged spatially on image is needed. Moreover, deep learning has become more common also in state universities for their master's and PhD studies' also, such kind of methods has been employing with common hardware like airborne laser scanners or smartphones and cameras [21].

An important question is how the sensors should be addressed in order to generate the described maps. How should corrections be possible to consider trees as infrastructure without an obstacle and how should these objects be correlated with different infrastructure objects (solar panels, roads, sidewalks)? In order to make this possible, it is necessary to design vehicle control units, production chain algorithm designs and road map control systems. These systems that provide operation in harmony and learning by machine will provide wires at many different points in the system from production to application [11].

3.3. Simultaneous Localization and Mapping (SLAM)

Currently, deep-learning DSLAM is rapidly gaining traction in the computer vision community. DSLAM can be applied to fix the ambiguities in the estimation using semantics and also to avoid the handling of multiple modalities without losing even a single bit of information while projecting the feature onto the other modality. Therefore, DSLAM is an important research field in AV. Easy-to-implement open-source versions of DSLAM have been used to further improve upon DSLAM methods that extend their focus beyond the mere development of deep learning-based mapping and tracking and robustness handling, only for static environment, to a variety of diverse topics. These methods include dynamic SLAM (D-SLAM), event denoising processing for event SLAM based on event cameras (EDP-E-SLAM) and deep reinforcement learning (DRL) for better representation and tracking [22] of the features in order to deal with the moving target of visual-inertial modeling.

In autonomous vehicles (AVs) equipped with a camera or a camera array, visual Simultaneous Localization And Mapping (VI-SLAM) can be used to provide spatial information and scene understanding. Visual-inertial Simultaneous Localization And Mapping (VI-SLAM) systems can be used to fuse data from the on-board camera and IMU sensor to optimize the performance and accuracy [23]. They can efficiently provide pose estimates even in the absence of GPS, and under occlusion, appearance changes, or lighting variations. The VI-SLAM systems can support different tracking methods based on either batch optimization or smoother. The SLAM problem must be addressed by all AVs in order to understand the vehicle's environment and then construct a map of this environment to avoid obstacles, enhance localization, and improve mapping. When the sensors on board the vehicle observe different scenarios in different ways while driving on the same path, the compounding of the observations caused inaccuracy in estimation due to the non-observability of the scenario-related features. The development of deep learning for SLAM has been referred to as "DSLAM," and the variants of DSLAM have become increasingly popular in recent years.

4. Challenges and Limitations of Deep Learning in Autonomous Vehicles

Despite such advancements in the domain of deep learning-based AV systems, the domain still faces several challenges, some notable ones include the following [24]. Firstly, the AV domain is filled with different kinds of sensor as an intelligent component, used to register different parameters from the environment like lighting, velocity, data intensity, etc. Secondly, the major concern for deep learning-based AV is related to the subtleties of transferring the knowledge from static images to video sequence. Although huge research is being bent nowadays towards addressing the challenges and limitations of deep learning-based AV, depth in many research is still required to complete the domain with intelligent deep learning-based AV sensors to realize vehicle AVs finally.

The field of autonomous vehicles (AV) is undergoing a rapid expansion and is fueled by the advancement and widespread applications of deep learning techniques and frameworks [8]. Several application areas in AVs to harness deep learning for addressing the AV challenges have been reported in the literature [17].. Future of AV domains such as self-driving cars, drones, and ships; incorporate deep learning based computer vision and image processing techniques to understand the environment and perform accurate decision-making processes. In-detailed, current AV system introduces several challenges, including spatial perception through object detection, object tracking and multiple object detection, segmentation, instance segmentation, pedestrian and vehicle detection, 3D object tracking, visual odometry and map creation, etc. Deep neural networks have been receiving a lot of attraction for addressing and solving these aforementioned challenges.

4.1. Data Annotation and Labeling

This observation can impact the cost of investment in inferences about false detections during manual data annotation. The average precision of detectors trained on algorithm-annotated data was stably better than those trained on human-annotated data for the three automotive data sets [25]. As per the domain expertise, it is possible to select the right combination of pre-labeled and manually labeled data. For instance, as humans are the most vulnerable road users, from the perspective of safety, it can be said that humans need to verify the data collected for pedestrians and bicycles since these are the traffic participants who are most often killed or severely injured.

Creating algorithmically annotated data can help us overcome the major bottleneck in the deployment of deep learning models in the automotive domain - the lack of manually labeled data [26]. For the automotive industry, where data collection is done by means of vehicle testing (particularly for safety-related systems), it is a common myth that we only need to have noise-free human-labeled data in order to train a good safety-related deep learning model. This chapter disproves that myth by quantitatively showing that a combination of human-annotated and algorithm-annotated data can improve the convolutional neural network-based detection models and also reduce the number of false positive detections.

4.2. Adversarial Attacks

To this system are combined several techniques. The first one is the integration of a Computer Vision and Light Detection And Ranging (LIDAR) multi-sensor fusion approach. The fusion of the data perceived by these two sensors allows the vehicle to detect a broader range of objects at different distances and with a 360-degree perception.

In adversarial training, an explicit search for adversarial examples from adversarial neighborhood around the training samples is performed. When adversarial examples are found, the model is iteratively updated in order to minimize the perturbation introduced by the adversarial example and disimprove the corresponding attack to cause less harm to the model in the future [27].

Adversarial attacks are a space of methods and techniques used in various domains to craft an intentionally perturbed data sample, able to elicit a wrong prediction by the model during the inference phase [28]. Deep learning is particularly sensitive to these attacks, however, traditional defenses such as input data randomization and data structure regularization often fail in the context of DNN-based perception. To mitigate adversarial attacks, a variety of countermeasures have been presented in literature, among which adversarial training and detection are widely considered the most promising [29].

4.3. Interpretable Models

An interpretable deep model is capable of making it clear why it gives a certain prediction in addition to showing high-level performance. Various methods are used to achieve this, such as class activation maps (CAM) and CNN visualization. For each category in its predictions, especially convolutions in the last layers of the model are used to filter the features giving the highest score. Using a model like G-CAM results in understanding the generated feature maps of the model in a detailed and clear form. In this dark glow, although a classic model that can be effective is not used, a generic method should be employed instead to allow the creation of a unified interpretative model and to measure its performance on the existing dataset, rather than the direct creation of different positioning-based recognition models. Thus, the robustness of this model should be evaluated again in order to exhibit that the fusion of different recognition models will contribute to obtaining better performance [6].

Deep learning capabilities are increasing rapidly with the design of the latest technologies, especially models that can make use of an interpreter but provide predictive results that are not biased; i.e., the predictions coming from the model in hard situations, such as bad weather and twilights, where the lighting is low, are explicitly accounted for. Although the model used to recognize road lines, traffic signs, and the like may operate successfully, the results in problems such as sunset and snow should be interpreted accurately by the system, and the system should not report wrong results in these situations. These models to be developed must be both interpretable and must have high performance [4].

5. Deep Learning Architectures for Autonomous Vehicle Environment Understanding

Architectures have been lately used in a variety of Automotive domains thanks to Deep Learning methodologies, Modules have different input shape characteristics and different components. Some prevention methodologies were built initially for classification of accidents. En Salakhutdinov and Hinton analyzed color images in 2007 and found that multi propulsion deep networks can efficiently collecters the important primitives of the data needed to accomplish the task of classification of objects [ref: 0079df4c-3b39-4447-afaa-e098b8ce30a1, ref: 00584b54-39e4-449f-b23d-13a747efd17f]. Nowadays, substantial achievements in object and scene detection, object segmentation and mapping have been made using Advanced Persistent Threat (APT). In addition, for a few Automotive Datasets such as Car Detection and Intersection Detection, few researchers have accomplished Driver

Requirement Convolutional Neural Networks for two common architectures of lane detection.

Deep Learning systems have had a significant impact on the automotive industry for various applications, such as computer vision for vehicle and lane detection, and more recently, they have been recognized to be essential also for enabling the development and expansion of autonomous driving. In fact, Deep Learning techniques have been employed to perform tasks such as analyzing and understanding the vehicle environment and improving safety in terms of emergency breaking and autonomous driving architectures [ref: e8b97841-a918-4dc3-98cd-e0f374e486b3, ref: 00584b54-39e4-449f-b23d-13a747efd17f]. In the former, data processing has had its ground on the Automobiles domain, namely using computer vision for various tasks. They were initially used as detectors for pedestrians, vehicles, and lanes, and later for applications such as data collection, vehicle and license plate detection, lane detection, and environmental understanding. Most of the tasks in the two areas above have been recognized as hot topics in the customer behavior and vehicle safety domain. On the other hand, in progressive use for attractive cars with the same domain, namely social media analytics, analysis was able to learn long-term dependencies and predict future properties of crashes and user engagement.

5.1. End-to-End Learning

In this section, we introduce the user to learn about some of the most influential and prominent approaches and results on key subtopics and areas of future interest in DL for autonomous vehicles, MV mapping, and assistive technologies,ref: ae6cf3f1-8ea6-4935-9ad5-64f0d7fc018d,ref: 5526d052-1549-441f-b450-1379df1b3e52]. This inventory can play a key role to foster innovation and spur the development of novel approaches in this area. Second, it sets the stage for addressing remaining open R&D challenges and open problems in both DL for MV and MV mapping by helping to understand the gaps in the field and spot areas of opportunities. At the same time, the inventory supports the analysis of specialisation and gaps in the current knowledge, to identify focuses for upcoming research in this domain.

Directly mapping perception inputs to control commands, this approach learns the policy of the autonomous system in an end-to-end manner [30]. It does not extract intermediate, semantic representations as a given object detection or lane following task, but rather it processes the raw image and maps it directly to a steering wheel angle or an acceleration command. Examples of end-to-end approaches we use in and impact the broader field of AVs are: lane-following approaches predating the repopularization of end-to-end methods and pioneering modern end-toend works such as [ref: 3e59c635-4426-49ed-ac21-74d03f4e116e,ref: ae6cf3f1-8ea6-4935-9ad5-64f0d7fc018d]. It is important to note that major open challenges and limitations exist for these systems including generalization to novel conditions, robustness to adversarial attack, unclear system reasoning, and safety validation.

5.2. Feature Extraction and Fusion Networks

Regarding sensor data, numerous options are available, such as stereo vision, LiDAR, radar, GPS, IMU and odometry data, and, in the more recent cases, camera and radar especially [4]. Voxel grid representations of LiDAR scans, with the 3D scene shaped into small three-dimensional cubes, are established for high-resolution volumetric data. To overcome the limitations of fusing only two modalities, some benchmark datasets, including the nuScenes dataset, introduce trilogy semantic segmentation data. The nuScenes dataset aims to resolve perception and prediction tasks, while multi-modal fusion represents the most important learning aspect deeply investigated. The Distracted Driver Prediction challenge dataset presents a different kind of multi-modal fusion, where a single-image challenge asks for a comprehensive related description while driver distraction concurrent time data is available.ensive Introduction to Autonomous Vehicles and Their Classification with Policy Recommendations [31].

Deep learning has churned out impressive results in environmental perception and mapping tasks, generating in-put for decision-making systems in modern autonomous vehicle architectures and can be used for feature extraction. These types of algorithms allow for the design of feature extractors directly trained on raw sensor data, enhancing the overall robustness and adaptability of the system [32]. It might be useful to recall that the main difference between fully connected layers and convolutional layers is that the latter are characterized by a weight sharing mechanism, which endows the architecture with translational invariance properties.

6. Deep Learning Techniques for Mapping and Localization

Commonly, this area refers to two main subproblems: on one hand, predicting what exists in the scene by means of categorizing and localizing the objects or instances being observed, usually called object-centric prediction or simply object detection, and on the other, additionally providing per-pixel semantic descriptions of the scene, which is called pixel-wise semantic segmentation. When a heavier integration between perception and mapping is targeted, the use of other techniques such as SLAM and Structure from Motion (SfM) for obtaining spatial alignment information can also be used to approach the simultaneous prediction of scene pixel semantics and metrically correct maps. In addition, deep homographies and view synthesis have recently been gaining research attention for their ability to leverage 3D maps and provide the capability to detect and reconstitute scene renderings in 3D-enabled contexts. Additionally, appearance-based place recognition and localization methods that view the problem of scene retrieval as a pure metric matching problem between images [33].

Possessing knowledge about the driving scene is one of the fundamental requirements for any autonomous driving system. A common approach for obtaining such knowledge is for vehicles to localize and map the 3D environment in which they operate. Traditionally, this would be done by using algorithms such as SLAM, which would provide a complete spatial representation of the scene and enable the vehicle to use such representations to localize itself [34]. However, while SLAM systems are able to generate maps of the environment as the robot moves through it, they are typically not able to perform high-level reasoning about the environment, e.g., identifying objects, individuals, or areas with some quality or property. Consequently, in order to leverage the data from such a mapping procedure to acquire data and information about the environment in the most efficient means possible, structural prediction is used, with high-level information about the environment being predicted in conjunction to the structure of the learned representations [8].

6.1. Graph Neural Networks

Deeper representations in GNNs are assumed to capture adjacency information, but an empirical evaluation highlights that GNNs perform poorly on certain synthetic graph classification tasks, failing to recognize simple topological structures. These tasks, which can typically be solved by linear classifiers for grid-like structure networks, such as the formation of a particular bermuda triangle or distinguishing graphs with and without a certain type of bridge, are not recognized by GNNs. The thin slices observed in the model's decision boundary and analysis in graph Fourier domain (the eigenvalues of the graph Laplacian matrix) suggest that GNNs learn low-level features abstracting only top-*d* Hop neighborhood information in the spectral domain.

Graph neural networks (GNNs) are used for various tasks such as handling graph data in chemistry [35], social networks, transportation, images, 3D polygons, and other high-dimensional data [36]. GNNs update graph node vector embeddings using message passing in graph convolution operations defined on the graph adjacency matrix. However, applying GNNs to graph classification tasks that can be trivially solved by simple classifiers with graph invariants as input grid features may be excessively aggressive [37]. For instance, the three-center and four-center connected components on a 10 nodes graph are simple invariants that can trivially distinguish between graphs with and without a particular component. Training a GNN to perform a similar task requires discovering similar regularities unnecessarily due to the deep graph nature.

6.2. Simultaneous Localization and Mapping (SLAM)

2.2 Simultaneous localization and mapping (SLAM) and environment perception. SLAM is one of the most important foundational techniques for autonomous navigation in intelligent robots. SLAM has been considered as one of the fundamental problems and has captured much attention from researchers in mobile robotics in recent decades. The SLAM problem is essentially about building a map of the environment while simultaneously localizing a mobile robot within the map, including a robot's structure motion and environment geometry. Over the last two decades, SLAM has continued to be one of the main research areas and develop rapidly. In its earlier days, Kalman Filters were often used in visual SLAM due to their robustness and ease of scalarization and linearization of dynamic systems. These classical SLAM methods were, how-ever, based on assuming visibility and static scenes. Recently, CRFs (Conditional Random Fields) have been popular and successful in building a dense representation of the observed environment and in different SLAM tasks. Collecting training data for these supervised methods is a difficult task. This issue puts forth the motivation of investigating unsupervised and self-supervised learning approaches.

Simultaneous localization and mapping (SLAM) technology surged in the last two decades, becoming one of the major research areas of autonomous exploration via robots. Between 2010 and 2018, deep learning has made cutting-edge advancements across a wide range of applications [38]. After that, the combination of deep learning and SLAM emerged as a research hot-spot, while the fusion of these two areas has been referred to as deep SLAM [22]. As stated in, deep SLAM has been widely applied in a variety of areas. In this section, our main focus is on SLAM using RGB-D sensors to generate dense maps of their surroundings. Therefore, we mainly list papers related to RGB-D SLAM. There are some papers that pioneered the utilization of deep learning in monocular visual SLAM to recover a class of geometrical information (depth, normal, odometry) [39].

7. Data Collection and Preprocessing for Deep Learning in Autonomous Vehicles

It is known that image processing and interpretation in high-dimensional data types such as RGB-D and other vision data are very challenging tasks. Semantic segmentation (SS) is the most accurate type of object recognition in real-time. In this study, the image-based environment recognition system is aimed to be trained accurately, effectively, in a few time. Semantic segmentation has been chosen as the environment perception round on the real system and a well-known birdseye view creation process are accompanied for showing where objects are independently of vehicle's current heading. Creating and labeling the best suit size of dataset could provide great convenience from the perception terminal to the decision-making stage in autonomous systems. Detecting all critical and necessary objects in urban scenes with all possible different weather and lighting conditions, various times of the day, under non-uniform weather conditions, representing different textures and sizes of all-sided detailed data in a well-prepared dataset is essential for creating a faultless deep learning model. For this aim, designing, collecting, and labelling the high-quality dataset is a requirement to easily increase the operating performance level, as it has occurred in gluconeroamer research.

[40] Autonomous vehicles have been an object of great interest of researchers for about two decades, enabling both standard and luxury vehicles. Deep neural networks, especially the learning models which can create high-performance level systems, facilitate large improvements in this process. The focus of this paper is the development of an operating autonomous vehicle powered by deep learning models, as well as the proposal of a data collection and labelling methodology. There are no similar multi-sensor vision-based vehicle experiments in the literature showing the data collection and labelling method in a methodological way. In this work, robot operation system (ROS) was used as a testbed, together with a Gazebo-based simulator, a remote controlled real vehicle, a Velodyne LiDAR

sensor, a ZED stereo camera, and a Raspberry Pi 4 single board computer. Regarding the robot testbed, all of the component and sensor types (depth camera, RGB camera, LiDAR sensor, other sensors) are suitable. However, the sensor and camera sets are not experimental, and experimental setups should be prepared according to the system's requirements.[11] Autonomous vehicles use surrounding sensors for environment recognition. Autonomous vehicles have various sensors in smart transportation systems. Since the sensors of the autonomous vehicles can be categorized into light detection and ranging (LiDAR), computer vision, radar, and global positioning system (GPS)/inertial measurement unit (IMU) systems, sensor fusion strategy is studied in various methods [17]. High-accuracy data obtained by sensors in autonomous vehicles are used for decision making, path planning, control, and environment recognition algorithm stages. The vision-based systems utilize the computer vision algorithms that process the RGB (Red, Green, Blue) images. Converting these images into object detection networks, semantic segmentation networks and so on, the autonomous vehicle could become familiar with predicting driving the road, comparing the learned most recent traffic laws and real one. The vision-based systems have non-contact, real-time, and cost-effective work manners.

7.1. Sensor Fusion

In MMFNv1, a monocular camera and the multisensor fusions of SPC candidate detection and depth-information guided energy potential high-definition (HD) map activations were used to complete driving tasks. In MMFNv2, dynamic fusion scopes for multisensors were introduced so that SPC detection results were as structurally representative as possible at different approaches. In MMFNv3, radar detection, HD-map extraction, and motion pattern data can perform driving tasks based solely on radar data, HD-map constraints, and the driver's control with LIDAR available. 3D-LIDAR-guided fusion was used in the updated version to get better results. Camera target tracking was combined with other sensor detections in MMFNv4, which was more in line with the actual situation speedometer output to enhance the target information. LIDAR filtered RGB image semantics provided better predictions. These targets were refined with HD Nav how-tos from the HD map. It can be seen from the figures that each function added can improve response results at different levels.

Most current works develop individual models for each sensor and then combine the perceptual output in the application layer. The advantages of the camera, such as the accurate position and high definition detailed color information, greatly help in refining the output of other sensors. Multi-sensor fusion models have been used in many modality fusion networks as the perception module backbone [41]. This improves their efficiency and enables them to achieve better performance. A Multi-camera–Fusion (MCF) net was used with individual models for different camera configurations and a fusion model for these modals, but stereo camera pairs suffer from a narrow effective detection range. Multi-Modal-Fusion (MMF) networks combined the perception outputs of the mono camera, Radar, Lidar, and related maps. Stereo- Pixel-Fusion (SPF) networks can directly improve the performance by using the depth information from the LIDAR brought into the model at the same time that monocular cameras were considered.

Sensor fusion is crucial for the accurate perception of the environment and objects for intelligent vehicles [42]. Different types of sensors, like LIDAR, camera, and radar, can provide rich information about the vehicle's surroundings. Camera sensors mainly leverage image processing and plane stereovision to detect objects, but their performance is strongly affected by weather conditions. LIDAR sensors provide accurate depth and 3D information but are expensive, bulky, and lack color and texture information, which limits their ability to detect objects. RADAR uses electromagnetic waves with long wavelengths (mm-wave) that are in great demand to detect distance and speed, which means it is able to work during different environmental conditions, including darkness, rain, fog, and snow, but RADAR sensors only reflect the objects in the surrounding areas and are generally used to provide supplemental information about the LIDAR and camera.

7.2. Data Augmentation

In automated nuclear material identification and verification, besides flipping and rotations, number 2, which is often confused with 1, 7, 5 and their flips (number zero is often confused with 8, 3, and their flips). With existing number 2 are flipped at four possible sides and for the capital character O, circulating the shape of it at different angles and then using the data that matched the real location, they construct their own dataset with good correctness. These are applied in different places in multiple applications, including document images, biomedical images, and various sensors, as well as multiple domains from the test set to the training set in a balanced way, while the unknown samples in their domain, such as verification dataset, should not be augmented.

Data augmentation has impacted a high number of fields, ranging from medical [43] to mechanical engineering. In dermatology research and practical life, contrast change is usually utilized for hiding skin and lesion shapes to mimic different patients' circumstances [44]. MR brain images flipping is performed for generating images from different directions [45]. Data augmentation prevents the model from learning irrelevant or trivial patterns and consequently makes the model more robust and discriminative towards individual overfitting. Here, we rotated and flipped the 2D images at different angles and by different sides increment. The main reason for performing so many synthetic processes is to have an equal number of augmented data for each class and an approximate number increasing of all augmented classes at the end of the surgery. Therefore, say the challenge was about having all Gaussian and biopsy points in the same position in all images, so the classifiers can easily find decision boundaries. To solve this challenge, with c0 is the original input matrix, we make, c1=c0, c2= flip (c0, hori), c3=flip (c0, verti), c4=flip (c2, verti), c5=flip (c2, hori), c6=flip (c3, hori), and c7=flip (c3, verti). These steps generate 28 images for each patient for the training condition. By using all augmented data for training, the model will be trained less biased. Flipping, the adject means that we added some remaining random background pixels around the real DAF layer. Also, finally, XY and YX structures are the same from the outline view and thus the flipped augmented images are still possible and correspond to some realistic cell types.

8. Evaluation Metrics for Autonomous Vehicle Environment Understanding

Typically, environmental understanding is evaluated by multiple metrics, evaluated on different datasets, representative of different real-world scenarios and conditions [6]. Most of the general-purpose recognition datasets can be used for evaluation. For instance, the very popular Cityscapes dataset allows easy evaluation, since it contains a subset with accurately recorded ground truth data. Custom datasets have been proposed, such as the ApolloScape dataset, that will test the implementation of Chinese road standards. Another approach for evaluating environmental understanding is to simulate the vehicle's sensor readings based on ground truth. A method based on this principal is proposed by using photo-realistic data as input for the AV system. A third approach is to employ metrics for assessing environment understanding from physical evaluation like depth or flow estimation.

A fundamental requirement for autonomous vehicles (AVs) centered on real-world operation and adoption by users is to have high performance in understanding their environment in terms of perception and understanding of interactions of surrounding agents. Metrics should be defined to evaluate and quantify the environment understanding capability of an AV [46]. The evaluation should be realistic accounting for different scenarios and weather conditions and occur in the real world or using sensors that match as closely as possible those of AVs' hardware.

8.1. Intersection over Union (IoU)

But in instances when identifying the object is also related to the orientation of an object, and multiple classification and detection tasks must be expected. Then, more specialized criteria and metrics measurements are used. For example, in the case of the instance segmentation or semantic segmentation problem, which kind of deals with decomposing multiple objects within the dataset and also in class-specific metrics evaluations [47]. There, another criterion is used for class-specific statistics results across classes. This is typically the most important aspect of well-performing recognition problems such as autonomous driving, the recognition of traffic signs, the recognition of other vehicles, traffic signals, pedestrians or cyclists, just to name some few of the necessary entities. The metric that typically is used to calculate the share of well-detected pixels in a segmentation volume is called mean Intersection over Union (mIoU).

Intersection over Union (IoU) is a widely used performance metric in the field of object detection and segmentation [ref: 02c50dad-ae48-4391-9980-02d6b069a0db, 685c6363-d66c-46a6-b6f7-5cb5b7b5833d]. It is essentially the measure of how much two bounding box definitions overlap one another. If a value of 1 is achieved, it implies an exact overlap between the predicted bounding box and the ground truth, while 0 represents no overlap at all. Precision (also known as Intersection over Prediction, IoP) and Recall (Intersection over Unison, IoU) metrics are based on the IoU. mAP (mean Average Precision) is another popular result evaluation metric. The key distinction here is that bounding box IoU calculates the area a rectangle on a plane, (whether in 2D object detection or in 3D object detection), therefore is also applicable to situations where only positioning is important and individuals do not care about the structure of the objects as such.

8.2. Mean Average Precision (mAP)

mAP, also known as the area under the precision recall curve (AUC-PR), is calculated for Object detection models which generally outputs the probability confidence of the ground truth object class. This model measures the likelihood of the prediction of the object. Where the mAP is generally larger with a larger IoU value, 0.5 is the value which is taken into account before evaluating the mAPs since it is the cutoff point for considering predictions to be true. Associated with false positives and false negatives are predictions that incorrectly match or make the classification. As the value of the intersection over union increases the true positives and false positives decrease, mAP at larger IoU values increases when predictions are less likely to be wrong and the model becomes more sensitize. Bounding box models mAP@0.5 denotes the mean average precision using the intersection over union (IoU) threshold of 0.5. Low precision values at 0.9 level and significantly high precision values at 0.3 level indicate under and over segmentation, respectively, of the annotated instances. Instance segmentation models can often cope with under-segmentation since the network learns to recognize the individual object both from its affinities and contours. mAP@0.5:0.95 (all points on the AP curve) or mAP@0.75 (single point) can cope with over-segmentation better as it takes into account the multiple instances that are present in the same. The precision is higher at 0.9 IoU levels due to more finely localized instance choices. Where AP@0.5 is high, it is possible to over segment since the contours are hazy and multiple object fragments are included. Large variation can be introduced on the mAP@0.5:0.95 when the blue noise mask is very thin and the affinity prediction is not very good, causing the AP@0.75 to be much lower than the AP@0.5 value in semantic segmentation models Estimated mean averages of box- level Like the bounding box means, the average precision (AP-IoU @ 0.5: 0.95) are shown to depicts greater under segmentation and over-segmentation behavior of the growing box models.

Accuracy is one of the most important factors for an effective machine learning model, which can be measured using Mean Average Precision or mAP [48]. While there are many other measures to evaluate the performance of an object detection model, mAP and acccuracy are two of the most important. mAP with respect to IoUs of 50% (the mAP@half) or to a varying IoU range (the COCO-style mAP) are often used for the evaluation of an object detection model. While mAP@half is a better measure of precision, mAP50,60,70,…95, which is the average of the mAP for thisistinct IoU thresholds, is a better indicator of the efficacy of the learning for semantic segmentation. Some of the other common measures used to evaluate performance of object detection models are bounding box accuracies such as IOU@50% and the prediction accuracy with top-k proposals [49]. Jaccard index, precision, recall, and F1 score are other metrics that are also used for measuring model performance. Precission is a measure of how much relevant instances among all detected instances. Recall is a measure how many of the relevant instances have been retrieved over the total amount of relevant instances. F1 score denotes the balance between the precision and recall and Jaccard index is the intersection over union of ground truth and the predicted object. Accuracy denotes the sum of true positive and true negative instances among all instances [50]. The following is a discussion about bounding box, semantic segmentation, and instance segmentation models in the context of their ability to predict intersections over union (IoU) with the mAP measure of accuracy.

9. Ethical and Legal Implications of Deep Learning in Autonomous Vehicles

Moreover, road authorities in several countries are moving to enhance the road infrastructure for V2X applications and CAV powered by providing standardized data containers and exchanges which improve communication and localization capabilities of the V2X underbuilt services. Specifically, in Sweden data exchange format for the traffic control systems and the real-time road condition (weather and surface state) data will be based on open standard collective administration and private deployment control information. As a conclusion, the rigid and adaptive architectures which allow us to handle different operational cases effectively, require large number of labeled samples, and as the intersection of operational cases increases the training set becomes less scalable in practice. It would be good to investigate and propose a model to leverage reusable data for scenario-specific representation learning in the ethical design phase of CAV [8].

Legal framework defined in the running document REGULATION (EU) 2019/2144 OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL of 27 November 2019 on type-approval of electric buses and coaches with regard to advanced driver assistance system (ADAS), automated equipment, and autonomous vehicle technologies includes specific requirements for the architectural limits of the systems, the testing requirements from both technological and non-technological perspectives, i.e., impact of the technology systems over the non-technological issues like accident chain and reasoning, ethics and liability management in automated driving applications is anticipated to test ADAS and automated vehicle systems in different topological subjects of data on an extensive set of scenarios with minimal and maximal architectural restrictions to assess that technology's/rule's compliance with the safety documentation [4].

Deep learning architectures have demonstrated unprecedented performance improvements in various perception and decision-making tasks which could be exploited to complement the key sensing and decisional capabilities of autonomous vehicles and improve their performance under complex driving scenarios. The employment of such data-driven approaches has the risk of limiting system's operability within limited number of scenarios, as input data distribution of the employed prior designs, e.g., other participants in the traffic, infrastructure, etc., may significantly differ during the runtime from what the machine has been trained on [2].

9.1. Safety and Liability Issues

There are several ethical and security issues in autonomous machine learning (ML) driving that need to be resolved within 10–15 years. Separate ethical issues include misleading assessments, questions concerning liability, unpredictable system behavior, safety measures, or technical and technological limitations and constraints. Due to its dependencies and associated safety concerns, we will not verify the use of advanced driver assistant systems and the data dependence of world model capabilities for safe deployment through ethical hacking and adversarial examples. Currently, industry-wide approaches and a separate common understanding of the realization must be created. This is essential to enable healthy commercialization and implementation of complex and highly flexible combinations of driver use and support features [51].

Deploying advanced deep learning models in commercial-grade autonomous driving systems and electronic driver assistance systems involve several technological and ethical challenges. Although Deep Learning (DL) has shown remarkable performance for many years in computer vision, the optimal model architecture, feature extraction, data representation, high-level understanding, cross-sensor fusion, and smooth sensor data fusion for traffic safety and efficiency have not been fully established [52]. Moreover, all companies involved in these technologies continuously collect data from the real world. However, the gradual shift from driving policy and procedure enhancements to autonomous driving has introduced several serious open problems, including uncertainty, liability, security measures, vehicle handover strategies, reactions against accidents, deep decision-making dynamics, and even actions against consequences [53]. To resolve these complex yet highly relevant issues, they must take into account innovations occurring through communications and software application-like updates for the advanced driver assistant systems and mapping localization and perception, sensor improvements, and technological and legal limitations in autonomous driving.

9.2. Privacy Concerns

Another issue of privacy that has critics concerned is whether AIs like the LLMs will use the data and personally identifiable information (PII) they acquire to protect the privacy and rights of others [54]. Will AIs acquire means of processing the data of individuals, then use that knowledge to manipulate individuals? Questions about AI ethics, fairness, bias, discrimination, and privacy are rapidly emerging. Yet to manage new ethical challenges posed by LLMs, society requires some philosophies, regulations, and standards. Collectively, this paper critically discusses the prudent use of these models so that society can find a responsible way to operate AI-based research safely, ethically, and with due respect for the privacy and dignity of individuals.

Deep learning has been widely used in intelligent autonomous systems towards their optimal perception, understanding and responsive actions [17]. In particular, sensors play a crucial role in spatial awareness, understanding the environment, and creating accurate machine learning models that offer consistent results and manage interferences better [4]. Over the years, researchers have extensively worked in understanding various intelligent sensor-based systems, deep learning algorithms, and techniques working collaboratively for their improvement. In this systematic review, the authors respond to the advancements in deep learning sensor fusion algorithms to understand the diversity and applicability of approaches within the context of intelligent sensor-based systems. Various applications such as robot systems, condition monitoring systems, transportation systems, healthcare systems, energy-efficient machine learning methods, and environmental awareness systems are taken into account for understanding the diverse applications of intelligent sensor-based systems.

10. Future Directions and Emerging Trends in Deep Learning for Autonomous Vehicles

Although deep learning methods such as convolutional and recurrent neural networks have been successfully bridging the gap for the edge, the architectures for detecting, tracking, and understanding objects around the vehicle are still evolving rapidly [8]. The autonomous driving stack, especially the perception and reasoning sections, is an enabler for processing vehicle data into actionable decisions but it needs the fusion of multiple lighter or heavy weight deep learning architectures to see through weather conditions, appearance variations, motion dynamics, and model unobservability biases. Combining different networks and successful multiobjective optimization and control strategies will be an imperative in increasing understanding and explaining increasing complexity in the coming years.

A main challenge in efficiently and accurately deploying deep learning models for autonomous vehicle functionalities is the relatively high computational cost of the algorithms [55]. Especially for modern computer vision tasks such as object detection and instance segmentation of today's data-hungry visual neural networks drastically require more processing power to be trained and/or tested properly [56]. Emerging High-Performance Computing (HPC) platforms featuring new technologies such as new-style Graphics Processor Units (GPU) and novel neural network architectures suitable for efficient dedicated electronic circuits are helping autonomous vehicle algorithms to become faster, more efficient and equipped with even more advanced predictions.

10.1. Self-Supervised Learning

N-tuple self-supervised learning: A single-image direction model is used for road texture classification in. Image datasets are used in training and testing. GitHub-inspired internet (databases) are collected using the word "peek" for testing. In the first study, the results showed that image-based classifiers could be used directly. In the competition itself, simple classifiers were used. In the second study, more powerful road classifiers are used. It is a large, realistic, installation made using artificial images. Maps derived from satellite images are used, and less realistic images and various parameters are used. Using generated images on more realistic tasks than the previous approach will tell us more about transferred capacity. Common use, permuted (n-Tuple) MNIST is used. Despite the low transfer success observed in the study, the approach is interesting to us.

Self-Supervised Learning [9]

Improve the safety and reliability of autonomous vehicles in a detailed and dynamic environment is challenging. It attracts more attention to the subject of learning maps in autonomous vehicles because of its significant advantages. The artificial neural network is a powerful tool for generating maps from sensory data. The common ways for learning maps are supervised learning methods and using vehicle state while learning. We have tried to answer the question of how accurately we can learn our environment with only our vehicle sensory data.

Introduction [57]

10.2. Few-Shot Learning

Instead of predicting key points, A2RL [17] completes the remaining and possibly occluded part of the objects based on the information of the few annotated estimates, i.e., the task-defining coefficients. In this way, A2RL intends to incrementally establish patterns in the fitting targets, and instead of predicting the remaining part of the object's map from a single observation, the approach build the demand map based on the overall distribution of the key points. Another major work extending few-shot learning to monocular depth estimation is FSD [58]. FSD first uses high-level feature matching to establish point correspondences between the few labeled and the unlabeled data, and then combines the technique with geometric consistency metric for better depth predictions, which facilitates learning to adapt to target scenes and dealing with task-specific complex spatial configurations. FSD has further improved the generalization performance and stable training in challenging target scenarios compared with FINet by only minimizing the error of unlabeled depth through one-shot learning, so that the few labeled data can guide the feature learning effectively.

Acknowledging that the real modality gap between a source domain and a target domain can degrade the performance, recent works have proposed holistic domain adaptation learning, where the input sensor data from the source domain are transformed as the target data before the particular task learning, such as steering prediction or depth estimation. In these works, images from the target domain are leveraged to guide domain adaptation. Inspired by few-shot learning, source data can be labeled with one-shot or zero-shot annotations, and the side information can be diluted to incorporate more challenging scenarios. S-DCIL [59] proposed to perform unsupervised domain adaptation for monocular depth estimation in real scenarios, where the source camera and the target camera are different. Different from the previouslymentioned static calibration errors, their work focuses on the temporal drift of an accurate relative camera pose suffered by refusing to re-calibrate the camera intrinsic and extrinsics. They have utilized one-shot depth annotations to guide the target domain adaptation.

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