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An Analysis Of Conventional And Deep Learning Methods For Object Detection In Autonomous Vehicles In Adverse Weather

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Abstract : The ability of computer vision technology to recognize objects and impediments, especially in inclement weather, is essential for improving Autonomous Vehicles' (AVs') environmental perception in intelligent transportation systems. Object-detecting systems, which are crucial to modern safety protocols, monitoring infrastructure, and intelligent transportation, face significant challenges under adverse weather conditions. AVs rely mostly on image processing algorithms for guidance and decision-making, which make use of a variety of onboard visual sensors. Even in bad weather, it is crucial to make sure that important components like cars, pedestrians, and road lanes are consistently identified. In addition to offering a thorough analysis of the literature on Object Detection (OD) in inclement weather, this paper explores the constantly changing field of AV architecture, the difficulties faced by automated vehicles in inclement weather, the fundamentals of OD, and the landscape of conventional and deep learning (DL) approaches for OD within the context of AVs. These methods are crucial for improving AVs' ability to identify and react to items in their environment. By successfully connecting these approaches with the developing area of AVs, this study explores earlier studies that used both standard and DL methodologies for the detection of cars, pedestrians, and road lanes. Additionally, this study provides a thorough examination of the datasets frequently used in AV research, emphasizing the identification of critical components in many environmental situations before summarizing the evaluation matrix. We anticipate that this review will aid researchers in better understanding this field of study.

Keywords: Intelligent transportation system; autonomous vehicles; object detection; deep learning; traditional approaches

1. INTRODUCTION

Every year, the World Health Organization (WHO) publishes data on the number of individuals injured in road accidents. Approximately 1.3 million people die and 20 to 50 million are seriously injured globally each year [1], with young men under 25 making up 73% of the fatal traffic accident victims. Improved intelligent transportation systems (ITS) with greater capabilities have been developed as a result of extensive research on the alarmingly high number of traffic fatalities. Autonomous vehicles (AVs) and automated driving systems (ADS) are the pinnacle of modern automotive technology. Artificial intelligence, computer vision, and intelligent transportation have all shown a considerable lot of interest in AVs, particularly self-driving cars [2]. Self-driving cars have had a more significant impact on the automobile industry than any other development since the invention of vehicles.

These methods aim to increase the accuracy and efficacy of object detection on streets and roads while resolving safety issues. Since it is a rapid and effective method of object examination, vehicle-based surveillance is an often employed approach. However, autonomous algorithms have always had trouble identifying things in bad weather, including rain, fog, snow, haze, storms, and poor lighting.

There are several detrimental effects of the weather on traffic and transportation. Globally, precipitation is recorded approximately 11.0% of the time [7]. Rainfall can unquestionably raise the likelihood of accidents by 70% when compared to normal weather, according to studies [8]. Furthermore, 77% of the world's countries get snowfall. For instance, according to US national data, icy, slushy, snowy, or slippery roads account for 24% of weather-related car accidents each year, while 15% happen when snow is falling or combined with sleet [9], underscoring the actual dangers of winter weather. Environmental factors as fog, haze, sandstorms, and intense sunlight significantly impair visibility, which poses serious challenges for drivers [10].

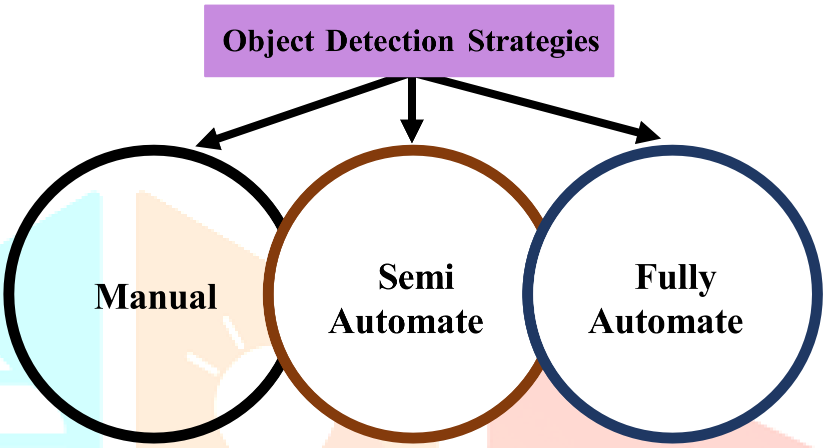

Figure 1. Object identification strategies

Traditional and deep learning (DL) algorithms are crucial for enhancing OD in autonomous vehicles, especially in adverse weather. While traditional AI, based on statistical learning, has been foundational, it faces limitations due to manual feature engineering and limited adaptability to dynamic environments, requiring extensive retraining and hindering its effectiveness in real-time applications.

DL offers a powerful alternative to traditional machine learning methods for OD in AVs, addressing the limitations of manual feature engineering and adaptability in dynamic environments. DL's multi-layer neural networks automatically extract features and learn from data, providing a more flexible and adaptable solution that enhances the performance of surveillance systems, self-driving vehicles, and smart city applications [11]. DL's neural network-based approach is particularly adept at handling complex models that traditional techniques cannot [12]. In AV object detection, hybrid models combining one- stage and two-stage detectors are effective, with two-stage models focusing on accuracy and one-stage models on speed, although the reasons for the latter's lower accuracy are not fully understood.

The research significance of this paper lies in its comprehensive analysis of the challenges and advancements in OD for AVs in adverse weather conditions. It provides a critical review of both traditional and DL approaches, offering insights into the limitations and potential improvements of the current detection algorithms. The paper contributes to the broader field of intelligent transportation systems by emphasizing the need for robust and reliable detection systems that can operate effectively in a variety of weather scenarios, which is crucial for the safe deployment of AVs in real-world conditions. Building on this significance, this paper also contributes to the discussion regarding AV architecture and challenges in adverse weather, and reviews the literature on detecting pedestrians, vehicles, and road lanes using traditional and DL methods.

It also summarizes common evaluation metrics for OD. In this paper, we contribute to the field by examining the fundamental architecture of AVs and the specific challenges they face in adverse weather conditions. We have compiled comprehensive datasets, leveraging real-world statistics from LiDAR and camera sensors, to provide a robust foundation for our analysis. We detail the core structure of OD systems and elucidate both traditional and DL methodologies for AVs. Building upon these approaches, we provide a critical review of the existing literature, focusing on the detection of three primary objects—pedestrians, vehicles, and road lanes—under challenging weather conditions. The structure of this paper is shown in Figure 3.

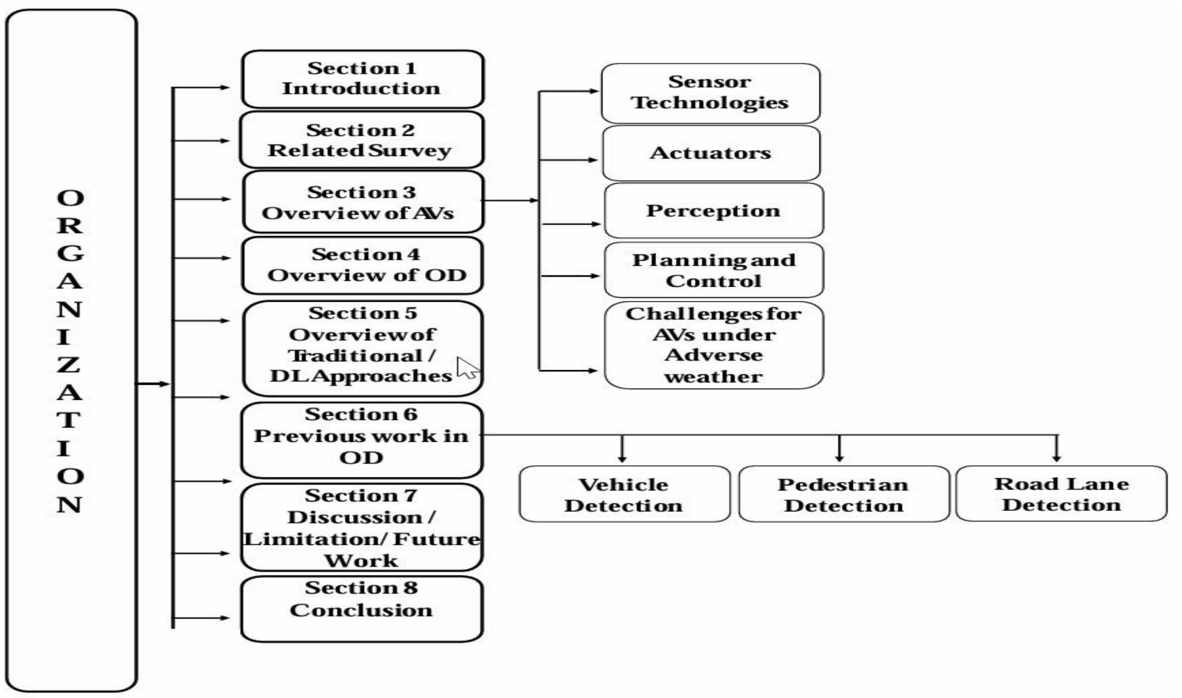

Figure 3. Paper organization, where OD = object detection.

2. AN OVERVIEW OF AV'S

The Society of Automotive Engineers (SAE) has established a classification system that divides Autonomous Driving Systems (ADS) into six levels of automation, ranging from Level 0 (No Automation) to Level 5 (Full Automation), as illustrated in Figure 4 [22]. This system is pivotal in understanding the evolution of autonomous vehicles (AVs), which are equipped with advanced sensors and software to navigate independently, thereby enhancing safety technologies and autonomy. Such a progression necessitates a collaborative effort among scientists and engineers across various disciplines to address the complex challenges associated with AV development [23]. The SAE automation levels provide a standardized framework that is critical for evaluating the capabilities and limitations of AVs at different stages of their development. By categorizing AVs into these distinct levels, it becomes possible to systematically assess the technological advancements and hurdles encountered at each level.

This structured approach is instrumental in setting realistic expectations about AV performance, shaping regulatory frameworks, and educating the public on the operational capabilities of AVs under various scenarios. Thus, the classification of AVs according to SAE levels is essential for advancing the field of autonomous driving, guiding its regulatory landscape, and informing societal understanding of these emerging technologies.

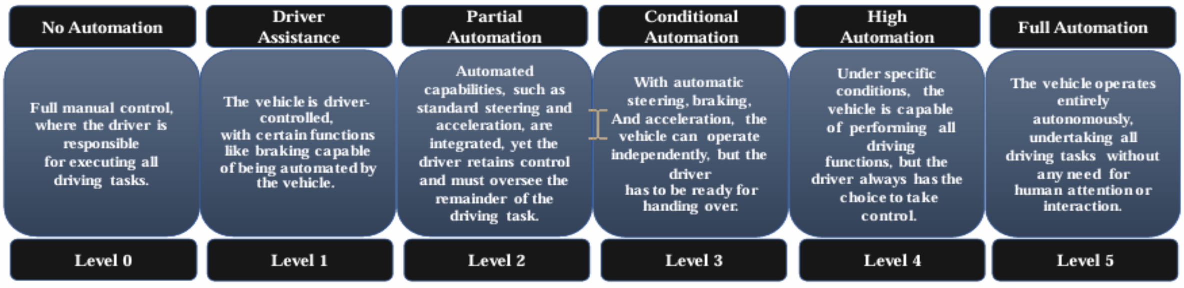

Figure 4. SAE automation levels for AVs.

This interaction results in an ongoing cycle whereby changes in the environment and vehicle states impact one another, highlighting the weather's crucial role in autonomous driving. Figure 5 shows the architecture of AVs.

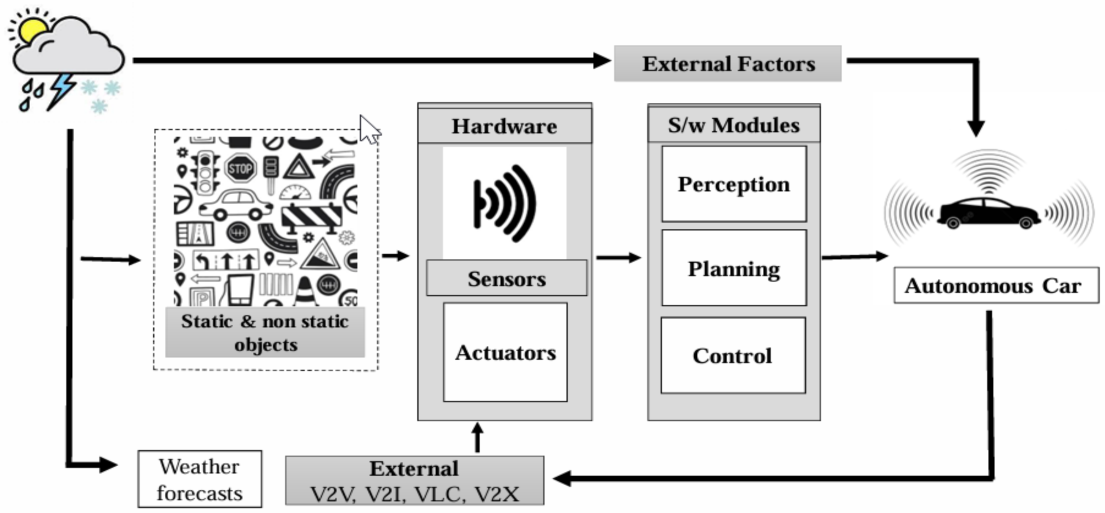

Figure 5. An architecture of AVs.

2.1 Sensor Technologies

In the pursuit of improving OD in inclement weather, selecting the right sensor technologies is essential to guaranteeing precise and dependable results. Unpredictable natural events, like adverse weather, might have an impact on the operating environment of AVs. These changes in the surrounding environment bring about differences in how AV sensor systems, which are the fundamental parts of ADS, operate. The main sensory elements used in AVs for perception are described in the section that follows, and the comparison of sensors is shown in Table 1.

Table 1. Comparison of sensors

Sensors	Advantages	Disadvantages
LiDAR	High resolution Long range Wide FOV	Sensitive to weather Expensive
Radar	Long range Detection of velocity Suitable for all types of weather	Low resolution Very sensitive
Camera	High resolution Detection of colors	Sensitive to weather Sensitive to lighting
Ultrasonic	Non-InvasiveReal-time feedback	Low resolution Expensive

2.1.1 LiDAR

LiDAR is considered the primary perceptive sensor in the self-driving car industry. Even though 3D-LiDAR has only been used in automobiles for slightly over ten years, it has already been shown to be crucial to the development of AVs and ADS [36]. Its exceptional ability to measure things precisely and its resilience to changing lighting conditions high- light how vital it is. Critical features of 3D scanning using lasers include its form aspect, affordability, tolerance to external variables, measuring range, precision, pinpoint density, scanning acceleration, configurational versatility, and spectral qualities [37]. These sensors work well in a range of weather conditions by using laser beams to measure distances and produce accurate 3D point clouds. However, there could be problems when there is a great deal of rain, snow, or fog since laser beams can disperse and potentially skew the data. Older types, such as the Velodyne HDL64-S2 [38], continue to function better in dense fog, while the performance of more modern laser scanners decreases. While making manual modifications can increase performance, it is still difficult to perceive reliably in deep fog. For this reason, alternative technologies, including gated imaging, should be considered for better performance in adverse conditions [39].

2.1.2 Camera

As the eyes and storytellers of automobiles, cameras are essential components of ADS. They are a crucial component of ADS, capturing the dynamic story of the surroundings, even though they are technologically more advanced than LiDAR. Installed on Windows, dashcams record continuously and have made a substantial contribution to the initial ADS datasets. Fisheye-lens professional camera setups nowadays increase the volume of data that may be collected. On the other hand, adverse weather can cause visual problems for cameras due to rain, snow, and fog. In low light, specialized cameras improve visibility, such as night vision versions.

The potential to overcome weather-related constraints in sensor fusion methods through the integration of these cameras is encouraging. The function of cameras will change further as autonomous driving technology develops, influencing sensor technologies and how they interact with the outside world. In summary, cameras are the storytellers of autonomous cars; they are sensitive to bad weather yet versatile enough to be essential to safer autonomous systems.

2.1.3 Ultrasonic

One typical vehicle sensor that is frequently left out of discussions regarding ADS is the ultrasonic sensor. Despite this error, it is positioned strategically on the vehicle's bumpers and throughout its body, making it indispensable for parking assistance and blind spot surveillance. Surprisingly, ultrasonic sensors have proven to be dependable and reasonably priced over a long period of time, which makes them a useful sensor choice . The frequency range of ultrasound sounds, which are audible only to humans, is normally between 30 and 480 kHz. In the field of ultrasonic sensing, the frequency range that is most frequently utilized is between 40 and 70 kHz. The resolution and sensor range are highly dependent on the selected frequency.

Longer sensing ranges are correlated with the lower ones. For example, the measuring range is up to 11 m, and the accuracy is one centimeter (cm) at the commonly used frequency of 58 kHz. Conversely, higher frequencies such as 300 kHz provide amazing resolution, maybe down to one millimeter, but at the penalty of a shorter range, capped at about 30 cm. Ultrasonic sensors are useful for close-quarters applications like parking because their normal operating range is 11 m . However, they can be used in autonomous driving; for example, Tesla's "summon" capability can be used to navigate garage doors and parking lots.

2.2 Challenges for AVs in Adverse Weather

Automation parts up to Level 3 have been added by automakers, and they rely on sensors and cameras. These devices function best in optimal conditions; thus, unfavorable weather presents obstacles. Weather has a major impact on AV performance, regardless of whether it is road-related or generic. A few of these effects are shown in Figure, and these are explained in more detail below.

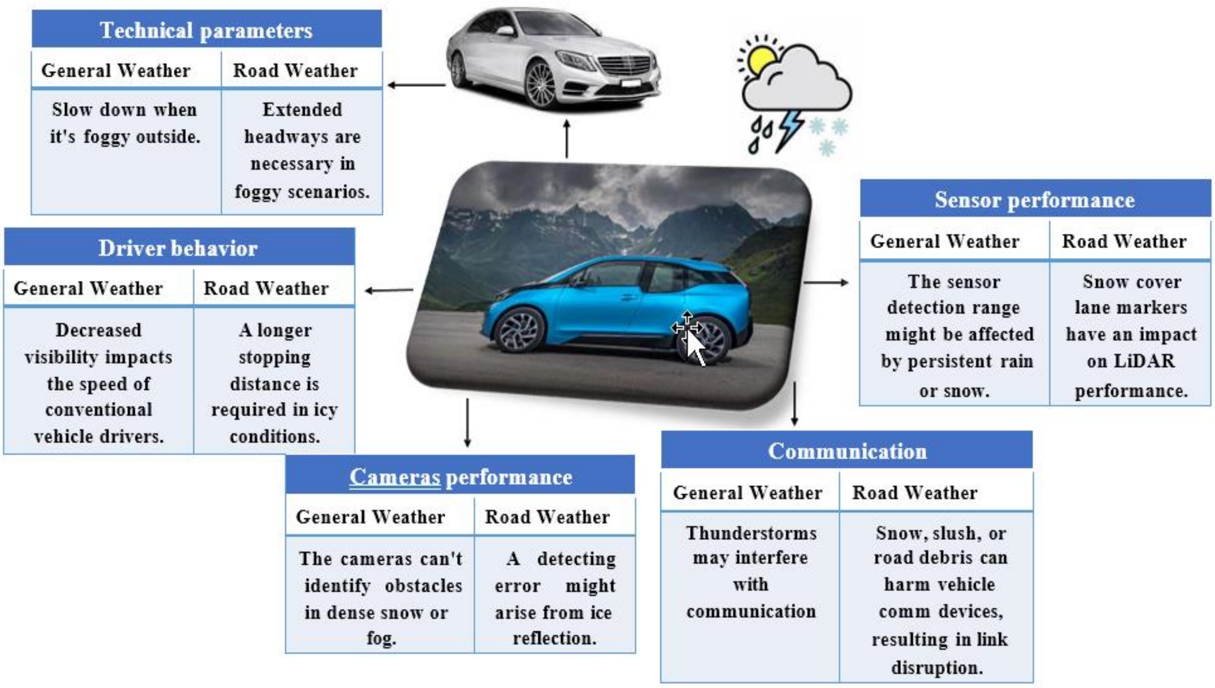

Figure 6. Weather impacts on AVs.

3. OVERVIEW OF OBJECT DETECTION IN AV'S

Most OD algorithms primarily adhere to a common framework, as shown in Figure 7. In OD, we have considered the following three issues:

1. Vehicle Detection: Vehicle detection is the process by which AVs identify and locate other vehicles on the road. This capability is crucial for AVs to make informed decisions about their own movement, such as maintaining safe distances, changing lanes, or responding to traffic situations.
2. Pedestrian Detection: Pedestrian detection involves the recognition and tracking of people walking near or crossing the road. This is a vital safety feature for AVs as it enables the vehicle to anticipate and react to the presence of pedestrians, preventing collisions and ensuring the safety of both the vehicle's occupants and those outside.
3. Road Lane Detection: Road lane detection is the ability of AVs to identify and under- stand the position and orientation of road lanes. This information is essential for the vehicle to navigate within its designated lane, follow traffic rules, and make correct turns, ensuring a smooth and safe driving experience.

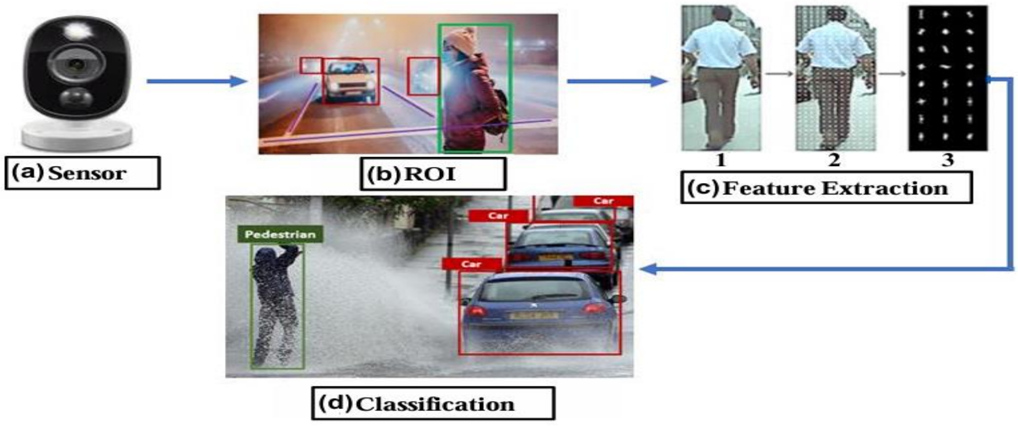

Figure 7. The basic framework for object detection systems.

Overview of Traditional and DL Approaches for Object Detection in AVs

The detection techniques are composed of three parts: the DL approach, the traditional technique, and a hybrid approach that utilizes both. The DL and traditional techniques are explained in detail in the section that follows. The performance graph of both approaches is shown in Figure 8.

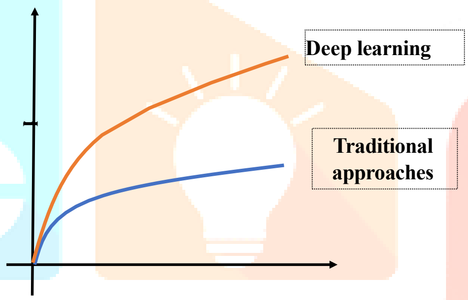

Figure 8. Performance graph of traditional and DL approaches.

3.1 Traditional Approach

Various algorithms were developed for the purpose of OD. Prominent traditional feature extraction methods include Scale Invariant Feature Transform (SIFT) , Viola– Jones rectangles , Haar-Like-wavelets and Histogram of Oriented Gradient (HOG) , Adaptive Boosting (AdaBoost), non-linear Support Vector Machines (SVMs), and linear SVMs, which are common classical approaches for object classification. A number of steps are involved in the SIFT algorithm , which is well known for its ability to determine scale and rotation-invariant features, making it resistant to partial occlusion, clutter, noise, and lighting variations. These include the detection of scale-space extrema, the localization of key points, the assignment of orientations, the creation of key point descriptors, and the final step of using key point matching to recognize objects. Descriptors are used to compare and identify items in a database using methods like nearest neighbor indexing and the Hough transform. Nevertheless, SIFT has some drawbacks, including the absence of ongoing key point consistency in dynamic objects, the significant dimensions of feature descriptors that can affect matchmaking, and some restrictions related to patents.

These AI techniques, which have their roots in statistical principles, have traditionally formed the basis of machine learning models. These techniques enable computers to recognize trends and forecast outcomes based on past data. However, even with their historical importance, traditional methods have clear drawbacks.

Reliance on manual feature engineering, as shown in Figure 9, in which experts carefully craft features for the model necessitates domain knowledge and frequently fails to capture the nuances of intricate datasets. Furthermore, these models' ability to adjust to unfavorable weather or dynamic surroundings is hindered by their inability to quickly incorporate new data without requiring significant retraining, which limits their usefulness in situations that change quickly. The development of more sophisticated methods, or DL approaches, to overcome these obstacles and improve the power of AI systems has been made possible by this realization of their limitations.

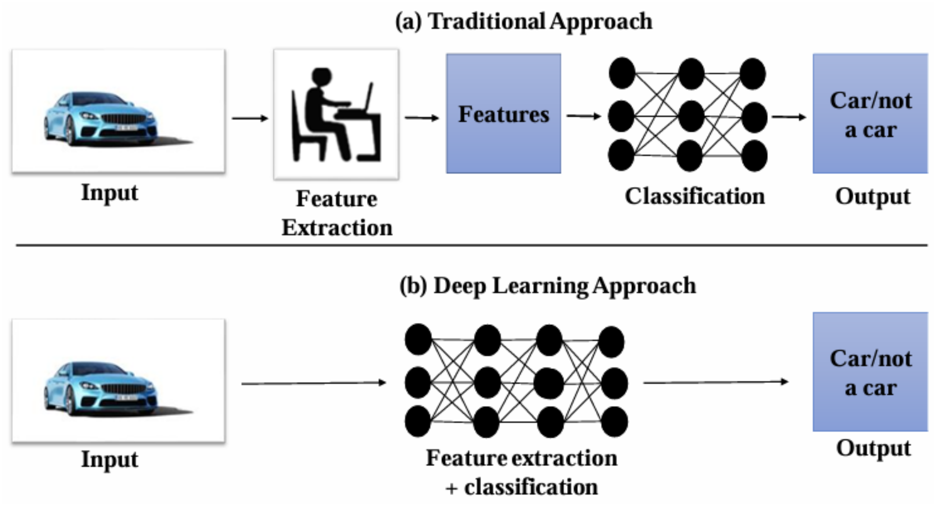

Figure 9. Primary structure of feature extraction for traditional and DL approaches.

3.1.1. DL Approaches

DL emerged as a subfield of machine learning and artificial intelligence in the 1990s . Unlike traditional methods, DL offers distinct advantages, including the ability to achieve higher levels of abstraction, improved precision, and faster execution. These advantages make DL a valuable choice for OD. The OD algorithm employing DL typically consists of three core components: a recurrent neural network (RNN), a depth belief network (DBN), and a convolutional neural network (CNN). Overall, object detectors based on CNN can be categorized into two primary types.

1. Single or one-stage detectors are known as the “non-regional proposal method” and “dense prediction”.
2. A two-stage detector is known as the “regional proposal method” and “sparse prediction,” as shown in Figure 10. In a single-stage detector, all the tasks are integrated into a unified system structure. Conversely, a two-stage detector separates the system into distinct stages for region selection, classification, and localization. Some regional proposal techniques consist of region-based CNN (R-CNN) , Fast R-CNN , Faster R-CNN , Spatial Pyramid Pooling Networks (SPPNet) , and Feature Pyramid Net- work (FPN). On the other side, the non-regional category includes Single Shot Multi-box Detector (SSD) , You Only Look Once (YOLO 1-8) , EfficientDet , Detection Transformer (DETR) , and Fully Convolutional One-Stage (FCOS). Since these methods constitute the foundation of CNN, they have emerged as the standard for OD. The amalgamation of one-stage and two-stage OD techniques has gained prominence in the field of OD within AVs. These hybrid approaches have demonstrated effectiveness across diverse scenarios, achieving promising results in precise OD and localization. Two-stage algorithms tend to deliver superior accuracy, while one-stage algorithms offer faster pro- cessing speeds. Notably, the reasons behind the lower accuracy of one-stage algorithms remain unclear. A study examining the drawbacks of one-stage algorithms, especially those with dense sampling, was conducted in. The study found that there was a major problem with the unbalanced background samples (negative instances) and foreground values (positive examples).

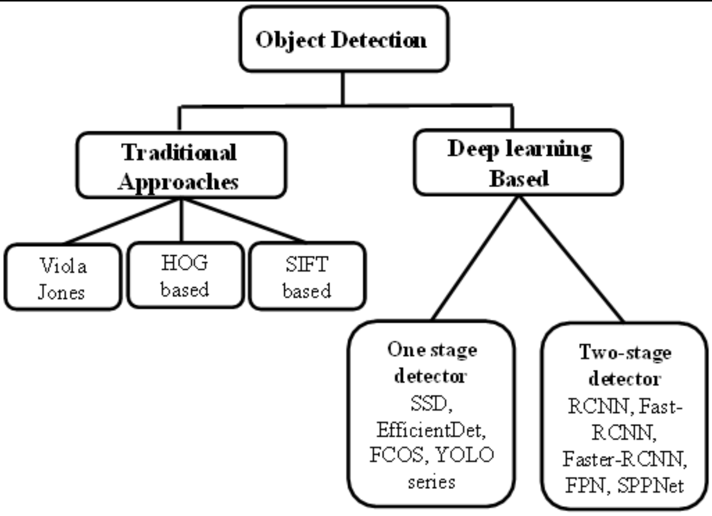

Figure 10. Traditional and DL approaches.

To solve this problem, the authors created Focal Loss, which alters the traditional cross-entropy loss function to give problematic cases more weight and thereby puts the emphasis on positive samples. After this adjustment, the RetinaNet network was created, showing better accuracy and quicker detection times than one- and two-stage methods. It should be mentioned too that the approach necessitates adjusting the focusing value, an extra hyperparameter [99]. However, the two primary state-of-the-art methods for DL-based detection these days are the YOLOv8 from the YOLO series (YOLOv1–YOLOv8) and the Faster R-CNN from the R-CNN family.

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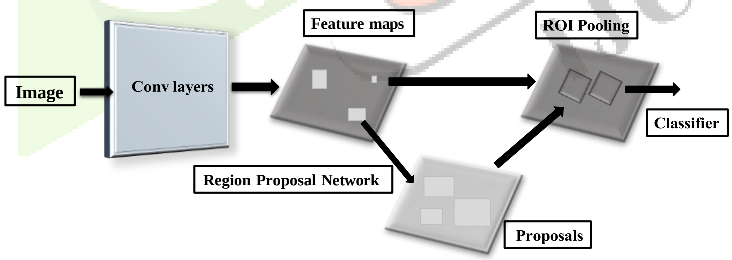

Figure 11. The architecture of Faster R-CNN [90].

AVs need to be able to identify moving items like cyclists, livestock, pedestrians, and different kinds of automobiles, as well as stationary elements like traffic signals, road signs, and parked vehicles because pedestrians are especially vulnerable and because AVs frequently and critically engage with other types of vehicles. This section focuses only on the previous literature using traditional and DL approaches for vehicles, pedestrians, and road lane detection.

Traditional Approaches for Vehicle Detection

Traditional vehicle detection techniques, which rely on appearance- and motion-based algorithms, have drawbacks, including being sensitive to changes in the camera's position, having trouble telling moving objects apart, and requiring a large number of photos to accurately identify motion.

Appearance-based algorithms that make use of features, such as HOG, Haar-Like, and SIFT, can improve identification, but they are vulnerable to exterior objects, adverse weather, and lighting variations. Even though they help to identify objects, biased classifiers like SVM and ANN might perform poorly in scenarios involving complicated traffic, which can result in false positives and make them susceptible to changes in the background, obstacles, lighting, and dimensions.

Year	Technique	Weather Classes	Accuracy
2014	SVM+PHOW	Rain, Fog, Snow, Low light	82.5%
2022	HOG–LBP	several weather	96.4%
2012	histogram GDVM	Rain, Night	92.4%
2019	tensor decomposition	Night	95.82%
2017	Particle Filtering	Dust, Snow	94.78%

Table 1. Vehicle detection previous work with traditional approaches.

3.1.2Traditional Approaches for Pedestrian Detection

This section delves into traditional techniques for pedestrian detection, comparing their effectiveness and limitations in various conditions. A notable study presents a method that leverages an infrared camera for nighttime pedestrian detection, combining Haar-Cascade and Histogram of Oriented Gradients-Support Vector Machines (HOG-SVM) to reduce false alerts, demonstrating the superiority of this approach in low-light conditions. Another study employed LiDAR point clouds and SVM for object clustering and classification in snowy environments, showcasing the robustness of this method for side-walk snowplow machines at night.

The real-world validation of this approach underscores its practical advantages over traditional vision-based systems in adverse weather. The work in stands out for its real-time pedestrian detection system (PDS) that uses stereo- based segmentation and SVM to distinguish pedestrians from objects with vertical edge features. The high speed and detection rate of this method highlight its effectiveness, particularly in dynamic scenarios where camera motion is a factor. Research addresses the challenge of detecting pedestrians from a moving vehicle in inclement weather, using SURF key points to compensate for camera motion and SVM for classification.

The impressive performance of this approach, as evidenced by its speed and detection rate, underscores the potential of hybrid feature extraction methods in complex environments. Another study combines Haar and HOG features to improve multi-person recognition and tracking, particularly in occluded and congested settings. The success of approaches in detecting both the side and frontal faces of pedestrians, as demonstrated through experiments on various datasets, highlights the limitations of single-feature approaches. The work in introduces a novel method for pedestrian recognition in hazy environments by integrating a dark channel prior haze removal model with HOG descriptors. The improved performance of this method over conventional HOG-based techniques on the 'INRIA' dataset indicates the benefits of adaptive preprocessing for robust detection in challenging conditions. With an emphasis on various weather situations, the study in presents a robust vision-based pedestrian detection system for intelligent transportation systems.

It incorporates feature extraction and SVM-based classification and addresses issues like variability and occlusions in real traffic photos. In a more constrained environment, the work in demonstrates a pedestrian recognition method using SVM and HOG features, achieving an impressive 98.00% accuracy in counting individuals in a limited field of view. This high accuracy, achieved through training on a dataset of 2000 road photos, underscores the effectiveness of the model in controlled settings, potentially outperforming other approaches that do not account for such precision. Another study provides a two-phase video recording pedestrian recognition method that combines local and global data with HOG features. The system's efficacy in pedestrian detection is demonstrated by increased detection rates and decreased false positives obtained through testing with the PETS 2009 dataset.

3.1.3Traditional Approaches for Road Lane Detection

In the study in lane detection and sliding-mode control (SMC) were employed to demonstrate a novel approach for autonomous tracking control in intelligent electric vehicles (IEVs). This method, incorporating an optimal preview linear quadratic regulator (OP-LQR) with SMC and a 2-DOF vehicle model, outperforms traditional controllers in route tracking and lane marking recognition. Additionally, it enables efficient allocation of unequal braking force to all four wheels, showcasing superiority over conventional methods. Addressing the challenge of adverse weather conditions, proposed a weather-resistant lane recognition method using horizontal optical flow, highlighting its capability for reliable obstacle assignment and lateral control essential for driver assistance and autonomous driving. Moreover, presents an adaptive lane marking identification method for low-light conditions, demonstrating its accuracy and robustness compared to existing techniques. Similarly, developed an advanced driver assistance system (ADAS) focusing on nighttime conditions, showcasing its effectiveness through successful highway tests. Lastly, Ref. [128] introduced a real-time lane detection technique for intelligent vehicles, highlighting its performance in complex road conditions and its potential for improving driving safety.

3.1.4 DL Approaches for Object Detection in AVs

DL has become much more popular and prominent than regular algorithms in recent times. This change in direction is attributed to DL's exceptional work, reliable outcomes, and breadth of industry experience. Jones and Viola introduced the well-known VJ infrared technology, which improved immediate detection efficacy and capabilities [84]. In their research [129], Romero and Antonio mainly concentrated on defining DL methods. Previous relevant research on OD, e.g., vehicles, pedestrians, and road lanes, is examined in this section under adverse weather.

3.1.5 DL Approaches for Vehicle Detection

A key element of ITS is vehicle identification, which is used in many applications such as traffic monitoring, ADAS, AVs, and traffic data. Robustness, acceleration, precision, and cost-effectiveness are the hallmarks of an intelligent system. For this, a variety of imaging sources are used, including satellite imagery, in-car cameras, UAV cameras, and traffic monitoring equipment. This study is mostly focused on on-road vehicle surveillance, wherein in-car cameras are essential. Nonetheless, there are a variety of difficulties in the field of vehicle detection.

There are several different classifications of vehicles, each having a distinct size, color, structure, and design. Additionally, they can be viewed at a variety of scales and positions, frequently in intricate traffic scenarios. Adverse weather conditions create extra challenges since they distort visibility and add noise to the sensors, which can result in missed objects and false alarms. This section will examine the major research works and methodologies that have influenced DL approaches for vehicle detection under adverse weather conditions, offering a basis for the discussion of novel strategies and developments in this crucial domain. Table 4 summarizes the previous work on vehicle detection under adverse weather conditions. One paper [130] underscores the efficacy of CNNs in image processing through a tailored methodology for multiclass weather image categorization.

Experiments with various batch sizes (128, 256, 512, and 1024) is recommended to enhance accuracy and generalization. Testing on larger datasets enhances classifier accuracy and widens learning scope. In the realm of two-stage detectors, introduces a practical approach for vehicle detection in challenging conditions like fog, low light, and sun glare, leveraging three trained CNNs (ResNet, GoogleNet, and SqueezeNet) with transfer learning. No- tably, ResNet achieves a validation accuracy of 100%, while GoogleNet and SqueezeNet achieve 65.50% and 90.0%, respectively. Additionally, Ref. employs Fast R-CNN for day and night vehicle detection, yielding impressive results under adverse conditions, validated by high recall (98.44%), accuracy (94.20%), and precision (90%). Furthermore, the on-road vehicle detection method proposed in utilizes multiple region proposal networks (RPNs) in Faster R-CNN to identify vehicles across diverse sizes and weather scenarios, outperforming the existing techniques with high average precision rates on various datasets, including DAWN (89.48%), CDNet 2014 (91.20%), and LISA (95.16%).

On the other hand, regarding one-stage detectors, another study [134] introduces an improved SSD-based front vehicle recognition algorithm for smart automobiles. Tested on the KITTI dataset, it achieves a high mAP of 92.18% and processes frames quickly at 15 ms per frame. The system enhances smart car safety in congested traffic and adverse weather conditions, prioritizing both accuracy and real-time performance. Another study enhances a YOLO-based algorithm for precise vehicle detection in foggy weather by integrating a dehazing module with multi-scale retinex. This enhanced model, trained with augmented data, surpasses traditional YOLO in foggy conditions. Additionally, Ref. proposes a modified YOLO model for on-road vehicle detection and tracking across various weather conditions. Utilizing a single CNN, it exhibits robustness and outperforms the existing techniques in intelligent transportation systems. Furthermore, Miao et al. developed a nighttime vehicle detection method using fine-tuned YOLOv3, outperforming Faster R-CNN and SSD in terms of accuracy and efficiency.

They achieved an average precision of 93.66%. Another study [138] utilized YOLOv4 with SPP-NET layers for ve- hicle detection, achieving an 81% mAP. In contrast, the study in focused on harsh weather conditions, introducing YOLOv4 with an anchor-free and decoupled head, albeit achieving a 60.3% mAP and focusing exclusively on a single class. Moreover, the goal of was to enhance self-driving vehicle detection in adverse weather using YOLOv5 with Transformer and CBAM modules, achieving an impressive mAP of 94.7% and FPS of 199.86. The DL approach proposed in for nighttime vehicle detection in autonomous cars, combining a Generative Adversarial Network for image translation and YOLOv5 for detection, achieved a high accuracy of 96.75%, significantly enhancing the reliability of AV recognition models for night conditions.

This study in [12] presents a DL-based intelligent AV weather-detecting system. Using a combined dataset from MCWDS2018 and DAWN2020, the performance of three deep convolutional neural networks was evaluated by categorizing six weather categories: overcast, rainy, snowy, sandy, sunny, and sunrise. The CNNs are SqueezeNet, ResNet-50, and EfficientNet-b0. The ResNet-50, EfficientNet- b0, and SqueezeNet models achieved 98.48%, 97.78%, and 96.05% accuracy, respectively, in the experiments, demonstrating remarkable accuracy rates while preserving quick in- ference times using GPU acceleration. By combining previously disparate datasets, the study's novel methodology makes a significant addition to DL applications for autonomous systems' weather detection.

4. DISCUSSION, LIMITATIONS, AND FUTURE RESEARCH TRENDS

4.1. Discussion

Recent literature highlights the increasing use of DL approaches for OD, yielding promising results under typical conditions. However, there is a pressing need for further advancements, particularly in adverse weather and complex scenarios. Enhancing OD in such conditions is crucial, especially for AVs, to prevent accidents and ensure safety. In the following discussion, we delve into the key insights and implications drawn from our research on OD in adverse weather conditions for AVs. Our research has explored both traditional and DL methods for AV object detection, focusing on vehicles, pedestrians, and road lanes. Traditional methods, despite their foundational role, struggle with high computational demands, slow processing, and occasional misidentification.

DL, on the other hand, excels by learning complex patterns from data, offering faster and more precise detection, especially in challenging weather conditions. This makes DL a more effective and adaptable solution for AV systems. Traditional vehicle detection techniques, which rely on appearance- and motion-based algorithms, face significant challenges in adverse weather conditions. Appearance-based algorithms like HOG, Haar-like, and SIFT are sensitive to exterior objects, adverse weather, and lighting variations, making them vulnerable in situations like heavy rain or fog. These algorithms often struggle to maintain accuracy due to the reduced visibility of vehicle features and the difficulty in differentiating vehicles from their surroundings. Motion-based detection methods, which track objects based on movement relative to the camera, also encounter issues in adverse weather.

4.2 Limitations

1. Our literature review primarily focuses on the detection of pedestrians, vehicles, and road lanes, which may not encompass all possible objects and scenarios relevant to AVs in adverse weather conditions. There may be other critical elements, such as traffic signals or animals, that warrant further investigation.
2. The detection algorithms discussed in our review may have inherent limitations, such as difficulties in detecting small or occluded objects, which could impact the accuracy and reliability of AVs in certain situations.
3. Our study primarily considers a range of adverse weather conditions, but there may be other environmental factors, such as dust storms or heavy fog, that were not extensively covered in the reviewed literature.
4. The field of AV technology is rapidly evolving, and new detection algorithms and sensor technologies may emerge that could significantly impact the findings of our review. Our study may not capture the most recent advancements in this area.
5. While our study includes datasets that simulate adverse weather conditions, the simulation environments may not perfectly replicate real-world driving scenarios. The complexity of real-world conditions, including unpredictable human behaviour and dynamic traffic patterns, can introduce additional challenges not fully captured in simulated datasets.
6. The ethical considerations and societal acceptance of AVs, especially in challenging conditions, are not addressed in our study. Public trust and the ethical use of AV technology are essential factors for their successful integration into smart cities.

4.3Future Research Trends

1. It has become more important to address the real-time requirements for OD in real- world applications. Deep neural networks, however, frequently require large amounts of computational power, which presents difficulties for embedded systems. To properly fulfil these objectives, resource-efficient technique development has become essential. To ensure the practical usefulness of the suggested methodologies, future research should focus heavily on their computational components, offering both quantitative and qualitative analysis.
2. The existing deep neural network techniques for difficult item detection mainly depend on large-scale annotated datasets. However, creating these databases is expensive and time-consuming. Consequently, there is an urgent need to create OD algorithms that can train with little to no labelled information.
3. The employment of various evaluation metrics and IoU criteria for OD in difficult situations has resulted in the absence of a clear benchmark standard, which makes comparing methods difficult. For future research in this area to be uniform and comparable, a global baseline must be established.
4. Creation of extensive simulation environments should occur that imitate inclement weather to thoroughly test and improve object identification algorithms.
5. To develop comprehensive solutions for adverse weather OD, researchers, engineers, and policymakers should collaborate more closely.
6. It is necessary to study the psychology and behaviour of human drivers in adverse weather, with an

emphasis on developing successful communication and trust with AVs.

7. Creation of novel tactics for the real-time modification of OD algorithms for AVs in response to changing environmental circumstances should be achieved.
8. Investigation into cutting-edge techniques for combining current weather data with weather forecasts to enable proactive decision making during unfavourable weather conditions is necessary.
9. Improvements in sensor fusion methods should be attained, which integrate information from several sensor types to provide more accurate and dependable identification in adverse weather.

10. To develop behaviour prediction models for AVs, leveraging machine learning and deep learning to forecast the actions of vehicles, pedestrians, and cyclists should occur. These models will operate effectively in adverse weather, improving AV decision making for enhanced safety and efficiency.

5. CONCLUSIONS

This paper reviewed the traditional and DL approaches for vehicles, pedestrians, and road lane detection in AVs under adverse weather conditions. We first studied the architecture of AVs with sensor technologies and other components and also discussed the challenges for AVs in adverse weather. After an overview of almost all the datasets related to AVs covering different weather conditions, we explained the basic structure of OD and the evaluation matrices used for it. Then, we explained the traditional approaches and DL approaches and discussed the traditional feature extraction methods that were prevalent for detection and classification but had limitations in adverse conditions. Manual feature extraction made them less suitable for complex applications. DL has become much more popular and prominent than regular algorithms in more recent times.

DL approaches explain the structure of YOLOV8 (one-stage detectors) and Faster R-CNN (two-stage detectors). Two-stage algorithms tend to deliver superior accuracy, while one-stage algorithms offer faster processing speeds. Notably, the reasons behind the lower accuracy of one-stage algorithms remain unclear. In addition, the statistics about the status quo of traditional and DL approaches for OD in AVs were provided based on the works collected in this survey paper. We found that DL was intensively used for vehicles, pedestrians, and road lane detection in AVs compared with the traditional approaches. Specifically, one-stage detectors were frequently used for vehicle detection compared with two stage detectors.

In addition, vehicle detection was frequently studied using both traditional and DL approaches followed by road lane and pedestrian detection. Finally, we presented a useful discussion along with some future research directions.

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