OBJECT DETECTION TECHNIQUES IN AUTONOMOUS VEHICLES, A SURVEY

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Abstract

This study deeply examines the object detection techniques in autonomous vehicles. As autonomous vehicle's core is object detection, which enables self-driving cars to precisely sense their environment and react appropriately to objects they detect. But in practical settings, developing a reliable and extremely precise system still presents significant difficulties because of restrictions such fluctuating ambient conditions, sensor limitations, and computational resource constraints. Degradation of the sensor in bad weather or low light, for instance, can significantly reduce the accuracy of detection. In this manuscript we have identified the limitations in existing work followed by recommendations. In addition, a detailed literature review is included regarding object detection techniques in autonomous vehicles following with an analysis of the current work.

1. INTRODUCTION

The World Health Organization (WHO) releases data on the number of injuries sustained in vehicles accidents each year. Every year, between 20 and 50 million people suffer serious injuries and over 1.3 million people die in car accidents globally with young males under the age of 25 account for 73% of these deaths. Thorough investigations into the alarming rate of traffic-related deaths have resulted in advances in Intelligent Transportation Systems (ITS) with enhanced features. Automated Driving Systems (ADS) and Autonomous Vehicles (AVs) are currently at the forefront of automotive technology. In the fields of computer vision, artificial intelligence, and intelligent transportation, autonomous vehicles (AVs), especially self-driving cars, have generated a great deal of interest. No prior invention has influenced the automotive sector as significantly as selfdriving vehicles. According to projections shown in Figure 1, the self-driving car market is expected to increase from 23.80 million units in 2022 to 80.43 million units in 2032 [1].

Figure 1. The global self-driving cars market size 2022–2032 in USD Million

Autonomous Vehicles (AVs) can benefit from AI analytics in a number of ways, including increased efficiency and safety [2]. This calls for reliable object detection across a range of settings. Autonomous vehicles' ability to detect and avoid objects is essential to their growth since it allows them to sense and comprehend their environment. Recognizing and classifying objects is crucial to AV systems' fundamental decision-making processes. Road safety and navigation are directly impacted by people, bicycles, and road signs. This entails improving object detection in AV contexts by utilizing a variety of Internet of Things (IoT) and artificial intelligence technologies. The evolution of obstacle avoidance in Autonomous Vehicles (AVs) has been significantly impacted by developments in sensor technologies, including as Light Detection and Ranging (LiDAR), radar, and cameras, which offer vital information for identifying and evaluating possible obstructions in the vehicle's path. These sensors provide vast amounts of data, which are then processed and examined by AI and machine learning algorithms to detect and categorize nearby obstacles. Computer vision plays a key role in obstacle avoidance by allowing it to observe and comprehend its surroundings. Using cameras and other optical sensors, AVs can comprehend and evaluate visual data from their surroundings thanks to computer vision, a branch of artificial intelligence. Artificial intelligence's field of computer vision allows AVs to use cameras and other optical sensors to comprehend and evaluate visual data from their surroundings. Computer vision algorithms analyze visual data to identify and detect objects in the route of a vehicle, including bicycles, cars, pedestrians, and other pertinent objects. Finding potential risks and impediments requires this. The capacity of deep learning-based techniques to extract complex patterns and attributes from huge datasets has made them well-known for object detection. Real-time decision-making algorithms, intelligent control systems, and sensor data processing enable obstacle avoidance. Strategies such as "You Only Look Once" (YOLO) are being employed more and more to improve AVs' ability to identify and recognize things on the road [3].

1.1 Survey Objective

This article endeavors to examine the object detection techniques which have been adopted in autonomous vehicles. Specifically, this review aims to achieve the following objectives:

1. Exploration of object detection Applications in Autonomous vehicles: This involves the investigation of real-world use cases in object detection.
2. We have explored object detection under different categories like using MATLAB tool box, YOLO software, adverse weather conditions, deep learning and YOLO NAS (Neural Architecture Search).
3. Predictive maintenance: In this survey, we have recommended to imply predictive maintenance techniques in object detection algorithms. Predictive maintenance has been made extremely difficult by the intricacy and risks of autonomous car systems. Regular maintenance should be carried out to ensure human safety because malfunctioning hardware and software in autonomous vehicle systems could result in fatal collisions. Large-scale product design for automotive systems depends heavily on anticipating future failures and adopting preventative measures to preserve system reliability and security.
4. Analysis: This survey paper ends with an analysis on the current work followed by recommendations and conclusion.

1.2 Paper Outline

The rest of the paper is organised in the manner listed below. Section 2 defines the working of object detection in autonomous vehicles following with predictive maintenance in section 3. In section 3 we have also given an overview of YOLO and performance metrics. The detailed literature is covered in section 4 in multiple subsections. Section 5 contains limitations in existing work following with recommendations in section 6. The conclusion is described in section 7.

2. HOW OBJECT DETECTION WORKS IN AUTONOMOUS VEHICLES

Autonomous vehicle sensors, data processing algorithms, and decision-making systems are seamlessly integrated to enable object detection. For autonomous driving, sensors like as cameras, LiDAR, and radar are used to gather real-time environmental data. In order to recognize and categorize items like pedestrians, cars, and road obstructions, this data is analyzed by advanced algorithms that frequently make use of deep learning and neural networks. After processing, the data is transmitted into the vehicle's control systems to enable functions including steering, braking, and acceleration. Self-driving car perception guarantees that vehicles can operate safely and effectively in dynamic contexts by continuously assessing and responding to their surroundings.

2.1 Key Components of Object Detection System

Autonomous vehicle object detection systems are made up of several essential parts that work together to ensure accurate perception and decision-making:

- Sensors: LiDAR, radar, cameras, and ultrasonic sensors provide a range of data, including visual pictures, depth perception, and object movement detection.
- Machine Learning Models: Sensor data is used by algorithms to recognise, classify, and track objects.
- Integration with Vehicle Systems: The smooth integration of object detection data with vehicle control mechanisms enables real-time responses to changing environments. By evaluating massive amounts of data from many sources, these systems provide coherent knowledge of the surroundings, ensuring that object detection for self-driving cars can operate safely. By evaluating massive amounts of data from many sources, these systems provide coherent knowledge of the surroundings, ensuring that object detection for self-driving cars can operate safely.

3. PREDICTIVE MAINTENANCE

Maintaining systems is essential to improve product efficiency and continuity. There are different types of system maintenance: reactive, planned, and predictive as depicted in Figure. 2 [4]. Reactive maintenance solely addresses system breakdowns or malfunctions. The issue is detected, and the necessary repairs are carried out. In order to prolong system life and reduce repair costs, planned maintenance entails routine inspections and maintenance tasks at predetermined intervals, regardless of whether the system has displayed failure symptoms.

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Predictive Maintenance (PM) uses advanced analytics on sensor data to predictsystem failures and optimize maintenance intervals, reducing malfunction time and increasing system reliability. PM has shown significant growth and advancements. Artificial Intelligence (AI) has been adopted in PM. AI based PM systems boost network efficiency and safety. Researchers are driven to focus on AI models and methods to enhance the autonomy and adaptability of intricate and dynamic wireless environments [5] [6].

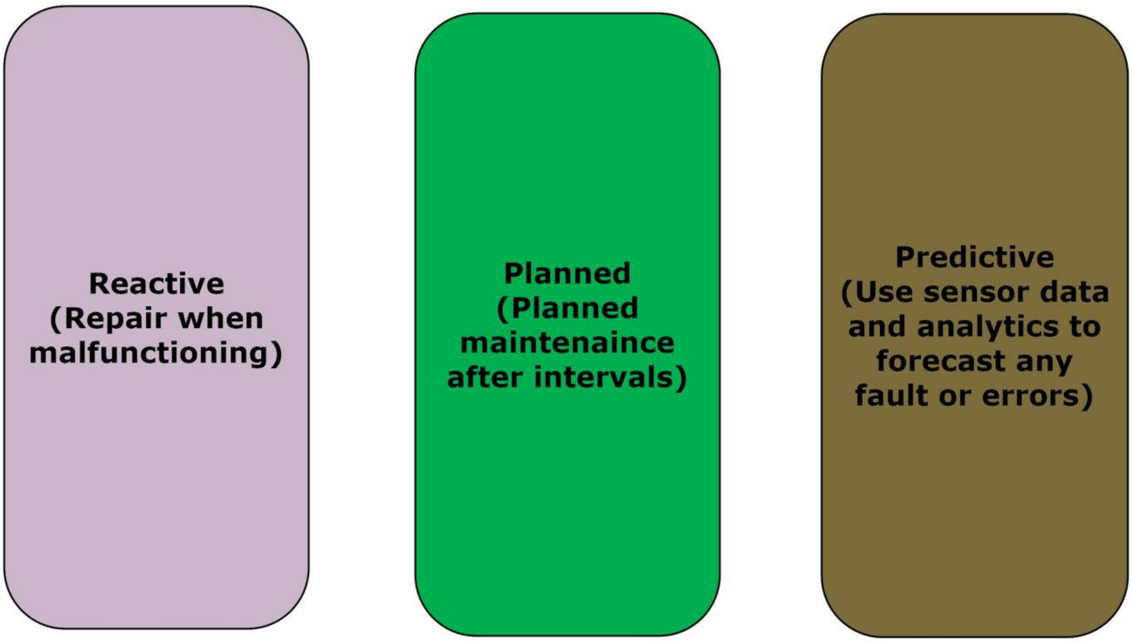

Figure 2. Different Types of System Maintenance

3.1 Predictive Maintenance in Autonomous Vehicles

Autonomous vehicles employ artificial intelligence (AI) to analyze their surroundings and make real-time driving decisions. Autonomous automobiles integrate data from multiple sensors to assess their operational environment and make real-time driving judgements [7]. Object detection is an important component in autonomous driving. Autonomous vehicles need to perceive their environment to drive safely and effectively. This perception uses object detection algorithms to identify nearby items, including pedestrians, automobiles, traffic signs, and barriers. Deep learning-based object detectors play a vital role in finding and localizing these objects. Missed object detection across subsets of data can have unforeseen effects, lowering the reliability, safety, fairness, and trust in machine learning (ML) systems. For instance, an image content moderation program might be very accurate overall, but it might not work well in certain lighting conditions or environmental effects. The key components of predictive maintenance are as follows.

1. Integration with IoT: Autonomous vehicle (AV) predictive maintenance system architectures rely significantly on Internet of Things (IoT) frameworks. IoT frameworks make it possible to gather data in real time and interpretation of data from a variety of car sensors, including those that track battery health, tire pressure, and engine performance [8]. Predictive maintenance with IoT integration makes it easier to monitor continuously and identify irregularities early. AV predictive maintenance systems use Internet of Things frameworks to gather information from a variety of sensors mounted all over the car, such as cameras, gyroscopes, and accelerometers. After being sent to a central processing unit, this data is examined using machine learning algorithms to find trends and anticipate any problems. Real-time monitoring and diagnostics are made possible by predictive maintenance systems that use IoT frameworks, allowing for early problem identification and prompt response. In addition to improving the safety and reliability of AVs, this reduces maintenance expenses and downtime.

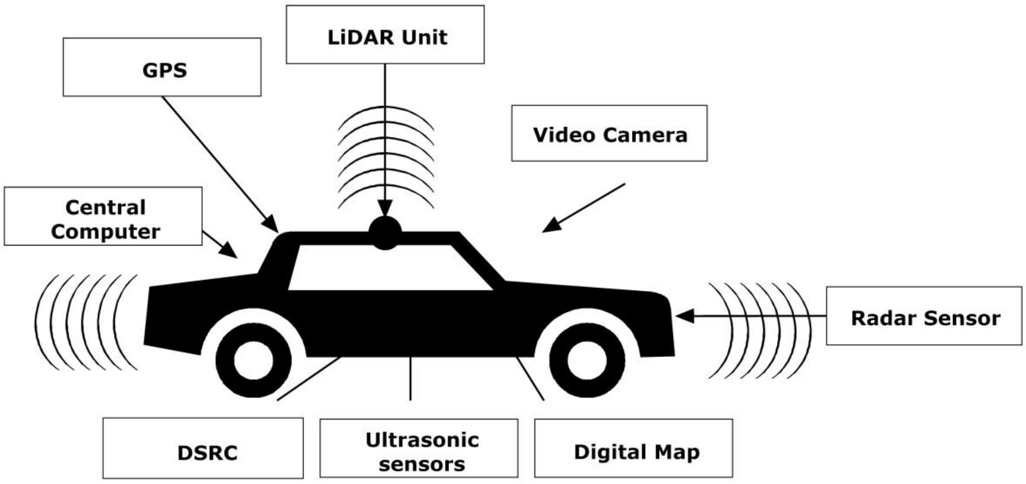

Figure 3. An illustration of Autonomous Vehicle Equipment

2. Sensor Networks: An Internet of Things (IoT)-based predictive maintenance system's sensors are usually tiny, wireless devices that are simple to put on equipment and cars. They have several sensing components that are able to identify modifications in the equipment's working circumstances. Through cellular networks, Bluetooth, Wi-Fi, and other wireless communication protocols, the data gathered by these sensors is sent to a central processing unit (CPU).

3. Real-time Monitoring IoT frameworks' real-time monitoring features are essential for improving the reliability and security of driverless cars. These frameworks allow for the early identification of any issues by continuously gathering and analyzing data from a variety of sensors and vehicle components. IoT frameworks reduce the risks associated with unplanned breakdowns by detecting any deviations from standard operating conditions in real-time and enabling fast intervention and corrective actions.

3.2 You Look Only Once , YOLO

In recent years, the convergence of computer vision and agriculture has led to significant advancements, ushering in a new era of precision farming and smart agricultural management. A central contributor to this transformation is the development of the You Only Look Once (YOLO) algorithm—a series of object detection models known for their remarkable speed and accuracy. Initially introduced by Joseph Redmon in 2015, YOLOv1 represented a breakthrough in object detection by enabling real-time processing. Unlike traditional two-stage detectors, YOLO employs a single-stage approach that divides an image into a grid and simultaneously predicts bounding boxes and class probabilities. This novel design significantly improved detection speed without compromising accuracy, laying the foundation for future iterations. As the YOLO series evolved, each version brought improvements that addressed the shortcomings of earlier models while introducing innovations in network architecture, training techniques, and optimization strategies. These advancements have been especially effective in overcoming challenges such as detecting small or occluded objects and enhancing performance across varied datasets. Collectively, the YOLO family has become a powerful tool in advancing agricultural applications through more accurate and efficient visual recognition systems.

3.3 Performance Metrics

- **Intersection over Union (IoU):** A higher IoU score indicates better localisation accuracy since it displays a better fit between the expected and ground truth bounding boxes. Its mathematical formula is shown below. It provides a value that reflects how closely the actual object position and the model's forecast match. An increased IoU score demonstrates a better fit between the predicted and ground truth bounding boxes, indicating improved localisation accuracy. The following is its mathematical formula.

$$IoU = \frac{AoO}{AoU} \quad (1)$$

In equation 1 AoO corresponds to area of overlap and AoU represents area of union. For instance, it facilitates object tracking and recognition in self-driving cars, thereby making driving safer and more effective. is used by security systems to identify and recognize objects or people in surveillance footage. IoU is used by security systems to identify objects or people in surveillance footage. In medical imaging, it helps to accurately identify anatomical structures and anomalies.

- Three essential measures are utilized to evaluate the effectiveness of object identification models: precision, recall, and F1-score. These metrics offer insightful information about how well the model recognizes objects of interest in images. These metrics are based on the following concepts.

1. True Positive TP: This is the case when the model performs perfectly. The IoU is above the threshold.
2. False Positive FP: The model identifies the object which does not exits. In this case the value of IoU is below threshold.
3. False Negative FN: The models does not identify the object despite of its presence.
4. True Negative TN: Not applicable in object detection.

- Precision: It is used to quantify the accuracy of the positive predictions made be the model. It is calculated using equation below,

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

- Recall: Recall evaluates the model's completeness in detecting objects of interest. A high recall score shows that the model correctly recognizes the majority of the relevant objects in the dataset. Equation (3) is used to compute it.

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

3.4 Loss Function:

YOLO ensures that the model correctly forecasts the bounding box locations, confidence scores, and class probabilities by measuring and balancing three components. These three components are: Classification loss, Localisation loss and Confidence loss. These values are balance so that the model performs efficiently.

4. OBJECT DETECTION IN AUTONOMOUS VEHICLES

In this manuscript, in-depth analysis of object detection techniques have been done in four contexts, first exploration of object detection applications using matlab tool box. Second exploration of object detection using YOLO. Third is adopting DL approaches in object detection and last is object detection in adverse weather condition.

4.1 Object Detection in Autonomous Vehicles using MATLAB TOOL BOX

Real-time object detection, identification, and tracking present significant challenges in the field of computer vision algorithm development. The ability to accurately recognize and identify objects from just one or two image frames is particularly essential for Advanced Driver Assistance Systems (ADAS) in modern vehicles [9]. These systems support drivers in detecting objects that might otherwise go unnoticed due to distractions, unfamiliar shapes, or adverse lighting conditions. Poorly designed algorithms can compromise safety, increasing the risk of accidents, especially in high-speed or congested traffic environments. To address these challenges, ADAS in autonomous vehicles must incorporate robust and adaptable object classification and detection techniques suitable for various driving scenarios. Beyond the automotive sector, object detection plays a key role in areas such as advanced robotics, security and surveillance systems, defense technologies, facial recognition, and space exploration. The algorithm in [9] was tested using 19 short video clips obtained from the Automated Driving Lab, covering scenarios such as sharp curves, highway ramps, and high-traffic conditions. It demonstrated superior performance in tracking vehicles, pedestrians, and lane markings when compared to the ACF (Aggregate Channel Features) detector. Additionally, the algorithm was evaluated using the Vision Sensor Dataset and during a full road test lasting over one minute. However, in situations involving low-light conditions or extremely congested roads, the algorithm exhibited certain limitations in accurately detecting and tracking objects. These challenges highlight the need for a sensor fusion approach, which combines data from multiple sources—such as vision cameras, radar, and inertial measurement units (IMUs)—to enhance the reliability and effectiveness of the vehicle's forward collision warning system. According to [10], object detection and recognition in computer vision typically involve four key stages: 1. Object classification within an image, 2. Localization of objects, 3. Detection of objects 4. Image segmentation. In addition to these steps, self-driving vehicles equipped with ADAS utilize advanced sensor fusion methods to identify and analyze features of both moving and stationary objects. Numerous detection algorithms have been developed based on fuzzy logic, statistical approaches, and neural networks. These methods often involve complex theoretical frameworks and require in-depth understanding, practical implementation, and extensive experimentation. To train and evaluate these algorithms, large datasets consisting of real-time images and videos are used. These datasets simulate real-world environments and help determine the distance and direction of objects relative to the vehicle. The detection and response mechanisms are integrated by combining feature extraction modules with decision-making or response models. An essential function of the system includes object counting, which estimates in real-time the number of objects present in a frame. Once the objects are detected, classified, localized, and counted, the algorithm proceeds to track them using the extracted features. Performing all these tasks in real-time requires highperformance computing hardware. In, [10] image segmentation is used to enable accurate object tracking without errors, implemented using MATLAB's automated toolbox. Table 1 shows the methods adopted in Matlab tool box.

Table 1. ***Comparison of Object Detection Approaches in Autonomous Vehicles in Matlab Tool Box***

Paper	Approach	Performance Metrics	Outcome	Drawbacks
[9]	19 short videos obtained from automated driving lab were tested	Performance compared with Aggregate channel feature detector in terms of reliability and effectiveness	The model outperformed ACF detector. It was recommended to use sensor fusion approach to enhance reliability and effectiveness of collision warning system	In AWC, the algorithm works badly. Missed detections are caused by lowquality pictures, particularly for objects that are distant.
[10]	categorises the barriers into three distinct threshold limit zones for response time, early detection, and warning.	provides an early detection of obstacles		

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4.2 Object Detection in Autonomous Vehicles using YOLO

The object detection in YOLO is illustrated in Table 2. The primary goal of the study paper [11] is to use the Novel YOLO algorithm instead of the Mobile Net algorithm for image classification in order to improve object recognition accuracy in autonomous vehicles. By combining the Mobile Net and Novel YOLO techniques, object identification accuracy was increased. The study involved two groups of 40 participants each, with each group undergoing 20 testing cycles. Statistical analysis was conducted using a 95% confidence interval and an independent sample T-test, with a power of 0.8. The alpha and beta values were set at 0.05 and 0.2, respectively. Sample sizes for both groups were calculated using the Clinical tool, with Group 1 applying the Novel YOLO method and Group 2 utilizing Mobile Net. The dataset was sourced from Kaggle. Results demonstrated a notable accuracy difference, with the Novel YOLO algorithm achieving an impressive accuracy of 88.6040%, surpassing Mobile Net's 72.5320%. To confirm the significance of this difference, an independent sample test was conducted, yielding a pvalue of 0.002. Since this p-value is below the conventional threshold of 0.01 (and 0.05), the difference is statistically significant. These results underscore the superiority of the Novel YOLO algorithm in enhancing object detection precision in autonomous vehicles compared to Mobile Net. The Novel YOLO algorithm significantly improved object detection accuracy, outperforming Mobile Net's 72.5320% with an impressive 88.6040% accuracy rate. To reduce the false detection rate of vehicle targets caused by occlusion, an improved method for vehicle detection in different traffic scenarios based on an improved YOLO v5 network is proposed. The proposed method enhances the network's perception of small targets by using the Flip-

Mosaic algorithm. A multi-type vehicle target dataset was constructed and collected in different scenarios. The dataset was used to train the detection model. According to the experimental findings, the Flip-Mosaic data augmentation technique can lower the false detection rate and increase vehicle detection accuracy [12]. As we have shown in our analysis section most of the research paper lacks in real-world diversity (heavy rain, snow, fog, night glare, dense traffic jams) is underrepresented. When perceptual results are not always achieved in autonomous driving applications, the lack of interpretability of neural networks can result in unanswered Safety of the Intended Functionality (SOTIF) questions. This research [13] offers an object detection algorithm to improve the accuracy of the perception system's detection in order to address the safety flaws in the current object detection procedure. Authors have used the well-known YOLO v5 one-stage object detection method as the baseline and assess their suggested model. The traditional YOLO v5 model is enhanced with a prediction extension box that takes into account the coverage area and redundancy of actual targets, ensuring the safety of image perception. The suggested object detection algorithm has been shown to improve the range of detected targets, which considerably improves perception safety throughout the autonomous driving procedure [13]. The main obstacle in the development of autonomous vehicles is latency. The delay between processing camera input data and the machine learning algorithm's decision to steer and move the vehicle on a safe road is known as the latency. Authors suggested a MobileNet SSD framework to solve these problems by connecting MobileNet and SSD, which makes it enough for real-time applications. The separable convolutions used in the model are stepwise separable convolutions and spatial separable convolutions. The outcome indicates how effectively our suggested MobileNet SSD model lowers latency and computational expenses. This study [14] discusses the application of YOLOv9, one of the most recent object detection models, in self-driving autonomous vehicle systems. Since selfdriving cars must operate in unpredictable traffic circumstances, precise and quick object identification is essential. In unpredictable contexts, classical techniques often suffer from sacrificing potential interaction in order to get the best fit and detection rate at any given time. The paper [14] YOLOv9, which offers precise detection with a faster speed in real-time driving settings, to get around such obstacles

Table 2. *Comparison of Object Detection Approaches in Autonomous Vehicles using YOLO*

Paper	Approach	Performance Metrics	Outcome	Drawbacks
[11]	The object detection accuracy was improved by using novel YOLO algorithm	Accuracy and confidence intervals	Accuracy/precision was improved using mobile net	Very small data set size was used
[12]	Accuracy in object detection was achieved using Flip-Mosaic algorithm to enhance the network's perception of small targets in YOLOV5	Accuracy and false rate detection	Flip-Mosaic data augmentation technique can lower the false detection rate and increase vehicle detection accuracy	Real-world diversity (heavy rain, snow, fog, dense traffic jams) is underrepresented.
[13]	The traditional YOLO v5 model is enhanced with a prediction extension box	Improved the range of detected targets, which considerably improves perception safety throughout the autonomous driving procedure	Prediction extension box is added to YOLO v5 which improves the range of detected targets which improves the perception safety	-
[14]	Yolov9 is used for object detection	accuracy	offers faster and more accurate	-

			detection in realtime driving situations	
[15]	self-supervised learning using the late YOLO versions	mean average precision	YOLOv5 and YOLOv8 outperform YOLOv7	YOLO models perform poorly in situations that are congested or occluded
[16]	YOLOv5 is proposed, featuring two complementary attention-augmented module	Mean Average Precision (mAP), recall	Improved performance in KITTI, BDD100K, IDD datasets,	Reduced performance in unfavourable weather circumstances

4.3 Object Detection in Autonomous Vehicles in AWC

The weather has a substantial detrimental influence on traffic and mobility. Globally, precipitation is observed 11.0% of the time on average. Research has unequivocally shown that rainfall can raise the likelihood of accidents by 70% when compared to typical conditions. Furthermore, 77% of countries worldwide get snowfall. For instance, US national statistics reveal that yearly, 24% of weather-related vehicle accidents occur on roads that are slippery, snowy, slushy, or icy, while 15% happen during active snowfall or a mix with sleet, underscoring the genuine dangers associated with snowy conditions. Drivers face serious difficulties when visibility is severely reduced by environmental variables as fog, haze, sandstorms, and bright sunlight. The rapid advancement of autonomous vehicles necessitates the integration of advanced sensing systems to effectively navigate the various challenges posed by road traffic. Although multiple datasets exist to aid object detection for self-driving cars, it is essential to assess their effectiveness under diverse global weather conditions. To address this need, a new dataset called the Canadian Vehicle Datasets (CVD), along with deep learning models that leverage this data [17]. The CVD consists of street-level videos captured by Thales, Canada, using high-quality cameras mounted on vehicles operating in Quebec. These recordings span both daytime and nighttime and encompass various weather scenarios such as haze, snow, rain, gloom, night, and clear sunny days. From the videos, 10,000 images of vehicles and other road elements were extracted, with 8,388 images annotated, yielding a total of 27,766 labeled objects across 11 distinct categories. We evaluated the YOLOv8 model trained on the existing RoboFlow dataset and compared its performance against a version trained on an expanded dataset combining RoboFlow with CVD. The inclusion of the proposed dataset resulted in improved accuracy metrics, with Precision, Recall, and mAP reaching 73.26%, 72.84%, and 73.47%, respectively. In the end, the model trained on this varied dataset showed enhanced robustness and offers substantial advantages for both autonomous and conventional vehicle applications, making it appropriate not only for Canadian settings but also for other regions with comparable temperatures. Harsh weather conditions and dynamic traffic scenarios create significant obstacles to accurately capture perception data, hindering advances in object detection technologies. This paper [18] offers a comprehensive review of object detection approaches under challenging weather conditions. It begins by exploring the difficulties caused by different weather effects such as rain, snow, fog, and varying lighting, all of which can greatly degrade detection system performance. Additionally, the study classifies current object detection methods into three groups: direct detection models, distributed models that perform image restoration (enhancement) before detection, and end-to-end models that combine image restoration and object detection in a single framework. A comprehensive evaluation of the advantages and limitations of each category is provided. Lastly, the study highlights the major challenges and potential directions for future research in this field. The integration of artificial intelligence (AI) into autonomous vehicles has revolutionized object detection, enhancing safety in complex driving environments. However, achieving accurate and efficient real-time object

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detection remains a critical challenge due to the diversity of objects and the need for rapid decision-making. This paper introduces the SCOPE (Stacked Classifiers for Object Prediction and Estimation) algorithm, designed to improve object detection capabilities in autonomous vehicles. The primary goal is to create a robust, highperformance model that accurately identifies various objects—including cars, trucks, pedestrians, bicyclists, and traffic lights—while addressing challenges related to detection accuracy and efficiency. Traditional object detection methods often struggle with inconsistent performance in dynamic, realworld conditions. These challenges call for advanced approaches to boost both the speed and accuracy of object classification in autonomous driving contexts. The SCOPE algorithm begins by prepossessing the Self-Driving Cars dataset, resizing images to 224 × 224 pixels, and normalizing the bounding box coordinates. The dataset is then split into training and testing sets, where two base classifiers—MLP and DL4jMLPClassifier—are trained. Their outputs are combined through a Random Forest meta-classifier in a stacked ensemble framework. The model's effectiveness is evaluated using standard metrics such as accuracy, precision, and recall. The SCOPE algorithm demonstrated strong performance on the Self-Driving Cars dataset, achieving 94 % accuracy, 91% precision, and 92% recall. Additionally, it exhibited low inference latency and a reduced false positive rate, ensuring reliable and consistent performance for real-time autonomous driving applications [19]. However each step in stacked classifier architectures depends on the previous classifier's output. The error spreads downstream if an early-stage classifier generates noisy feature estimates or makes a wrong prediction. Object detection and classification are vital for the safe and efficient navigation of autonomous vehicles, especially in the complex environments typical of Indian roads. This paper [20] focuses on developing robust detection and classification algorithms tailored to the unique challenges found in India, including diverse traffic patterns, unpredictable driving behaviors, and varying weather conditions. Although considerable advancements have been made in object detection for autonomous systems, many current methods struggle to adapt effectively to the conditions prevalent on Indian roads. To address this, we propose a novel solution based on the YOLOv8 deep learning model, which is lightweight, scalable, and optimized for real-time deployment using onboard cameras. Our experimental evaluation involved real-world scenarios featuring a wide range of weather and traffic situations. Videos captured from different environments were used to test the model's performance, specifically Page 8 of 15 F1000Research 2016 - DRAFT ARTICLE (PRE-SUBMISSION) measuring accuracy and precision across 35 object categories. Results showed a precision score of 0.65 for detecting multiple classes, underscoring the model's capability to identify a broad spectrum of objects. Additionally, real-time testing achieved an average accuracy above 70% in all scenarios, with peak accuracy reaching 95% under ideal conditions. The evaluation criteria extended beyond standard metrics to include factors particularly relevant to Indian roads, such as poor lighting, occlusions, and erratic traffic behavior. Overall, the proposed approach outperforms existing methods by striking an effective balance between model complexity and detection performance. But the top-performing model (YOLOv8-Nano, 20 epochs) obtains recall of only 0.50 but precision of 0.65.This implies that many items are overlooked, which is crucial for autonomous driving. In order to enhance feature extraction and highlight important features in weather-degraded scenes while preserving real-time performance, this paper [21] introduces YOLOv11-TWCS, an improved object detection model that combines TransWeather, the Convolutional Block Attention Module (CBAM), and Spatial-Channel Decoupled Downsampling (SCDown). Authors method combines optimised network architecture with adaptive attention mechanisms to tackle the dual problems of weatherinduced feature degradation and computational efficiency. Assessments on the DAWN, KITTI, and Udacity datasets demonstrate competitive performance versus other cutting-edge techniques and enhanced accuracy over baseline YOLOv11, with mAP@0.5 of 59.1%, 81.9%, and 88.5%, respectively. In order to improve security and reliability, future research will concentrate on resolving issues in congested or cluttered settings and expanding adaptability to more extreme

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weather conditions. All of these techniques are summmarized in Table 3. The study in [22] tackles the problem of accurate object detection in foggy conditions, which is a significant challenge in computer vision. We introduce a new method utilizing a real-world dataset gathered from various foggy weather scenarios, emphasizing different levels of fog density. By annotating the Real-Time Traffic Surveillance (RTTS) dataset and employing the YOLOv8x model, we thoroughly examine how fog density affects detection accuracy. Our results show that the YOLOv8x model attains a mean average precision (mAP) of 78.6% across different fog densities, surpassing existing state-ofthe-art techniques by 4.2% on the enhanced dataset. Furthermore, we demonstrate that increasing dataset diversity substantially improves the model's ability to detect objects in difficult foggy conditions. This work advances object detection technology specifically designed for foggy environments, with important applications in areas such as autonomous driving and surveillance, enhancing both safety and operational efficiency. For conducting research under adverse weather conditions, quantitative fog measurements and sensors meteorological calibration is mandatory. This research paper [23] focuses on improving the performance of object detection by utilizing YOLO versions 5, 7, and 9 in adverse weather conditions (AWCs) for autonomous driving. Although the standard hyperparameter settings are effective for clear images, fine-tuning is essential for AWCs. Given the vast number and diverse range of hyperparameters, determining the optimal values through trial and error is challenging. To tackle this issue, the study employs three optimization algorithms—Gray Wolf Optimizer (GWO), Artificial Rabbit Optimizer (ARO), and Chimpanzee Leader Selection Optimization (CLEO)—to independently refine the hyperparameters of YOLOv5, YOLOv7, and YOLOv9. The findings indicate that these optimization techniques significantly enhance the performance of the YOLO models for object detection in AWCs, achieving an overall improvement of 6.146%, a 6.277% enhancement for YOLOv7 when combined with CLEO, and a 6.764% increase for YOLOv9 when paired with GWO. When GWO, ARO, and CLEO are used for hyperparameter optimisation, training time and computational complexity are greatly increased. Since YOLO models must be retrained for several epochs with each optimisation cycle, the method is less appropriate for deployment situations with limited resources or real-time. This paper [25] presents a comprehensive examination of object detection strategies designed for self-driving cars, covering both conventional and deep learning-based strategies as well as new developments. In order to illustrate their shortcomings in managing intricate real-world situations, authors by looking at traditional methods like Haar cascades and Histogram of Oriented Gradients (HOG). Authors then examine cutting-edge deep learning models, such as Convolutional Neural Networks (CNNs), Region-based CNNs (R-CNNs), You Only Look Once (YOLO), and Single Shot Detectors (SSDs), assessing their precision, speed, and resilience under various driving scenarios. Additionally, the study investigates the use of sensor fusion techniques, which combine information from radar, LiDAR, and cameras to improve detection reliability. Potential solutions are discussed, along with difficulties including occlusions, bad weather, and real-time processing limitations. Authors also examine how evaluation criteria, annotation techniques, and dataset quality affect model performance. The study concludes by outlining potential future paths, such as the use of edge computing, transformer-based designs, and continuous learning to increase adaptability. In order to satisfy the changing requirements of autonomous driving systems, this thorough overview attempts to assist researchers and practitioners in choosing and developing object detection techniques. Although this is a review paper but it does not consider object detection under adverse weather conditions. Autonomous vehicles (AVs) must be able to identify and recognize things in their environment, even in inclement weather, in order to achieve the highest level of automation. Sand weather makes it extremely difficult to detect objects because of environmental factors such opacity, low visibility, and shifting lighting. The performance of various activation functions in sandy weather was assessed in [26] using the You Only Look Once (YOLO) version 5 and version 7 architectures. Their performance was assessed using mean average precision (mAP), recall, and precision.

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Although authors used only sandy photos, they used the Detection in Adverse Weather Nature (DAWN) dataset, which includes a variety of weather situations. Additionally, utilizing a variety of augmentation techniques, including blur, saturation, brightness, darkness, noise, exposer, hue, and grayscale, authors expanded the DAWN dataset and produced an augmented version of it. According to their findings, YOLOv5 with the LeakyReLU activation function outperformed other designs in the original DAWN dataset in terms of the documented research findings in sandy conditions, achieving 88% mAP. YOLOv7 with SiLU obtained 94% mAP on the expanded DAWN dataset that we created [26]. In this manuscript the PM for cameras, LiDAR, radar, sensors need to be consider [26].

Table 3. ***Comparison of Object Detection Approaches in Autonomous Vehicles in AWC***

Paper	Approach	Performance Metrics	Outcome	Drawback
[17]	This study introduces an extensive dataset containing 8,388 annotated images of various vehicles	Precision, Recall, and mAP	Improved precision, recall, robustness and mAP.	-
[19]	Proposed the SCOPE (Stacked Classifiers for Object Prediction and Estimation) algorithm, designed to improve object detection capabilities in autonomous vehicles.	accuracy, precision, and recall	The SCOPE algorithm demonstrated strong performance on self-driving cars ensuring a reduced false positive rate.	Each step in stacked classifier architectures depends on the previous classifier's output. The error spreads downstream if an earlystage classifier generates noisy feature estimates or makes a wrong prediction
[20]	This paper [20] focuses on developing robust detection and classification algorithms tailored to the unique challenges found in India, including diverse traffic patterns	Average accuracy and peak accuracy	Precision and accuracy was improved using YOLO v8	The top-performing model (YOLOv8-Nano, 20 epochs) obtains recall of only 0.50 but precision of 0.65. This implies that many items are overlooked, which is crucial for autonomous driving
[21]	introduces YOLOv11-TWCS, combines TransWeather, the Convolutional Block Attention Module (CBAM), and Spatial-Channel Decoupled Downsampling (SCDown)	mAP	Improved accuracy	Future work is resolving issues in congested and cluttered areas.
[22]	The study in [22] tackles the problem of accurate object detection in foggy conditions,	a mean average precision (mAP)	-	For conducting research under adverse weather

	which is a significant challenge in computer vision.			conditions, quantitative fog measurements and sensors meteorological calibration is mandatory
[23]	This study applies three optimization algorithms GWO, ARO and CLEO for training hyperparameters	Performance	achieving an overall improvement	increases training time and computational complexity since YOLO models must be retrained for several epochs with each optimization cycle.
[24]	Latency was reduced using mobile net and SSD	Latency	-	Lack of model training details
[25]	Comprehensive examination of object detection strategies designed for self-driving cars.	The study concludes by outlining potential future paths, such as the use of edge computing, transformer-based designs, and continuous learning to increase adaptability		The detection of objects in inclement weather is not discussed in the paper.

4.4 Object Detection in Autonomous Vehicles in Deep Learning

Table 4 and table 5 show the literature review of object detection using deep learning. Summary of the all techniques is mentioned in Table 6.

Table 4. ***Comparison of Object Detection Approaches in Autonomous Vehicles in DL***

Paper	Approach	Performance Metrics	Outcome	Draw back
[27]	Nighttime Human Detection Using CNN	Nighttime Human Detection Using CNN	Detection Accuracy, False Negative Rate	Limited Visibility
[28]	DL Methods for Detecting Adverse Weather	Detection Reliability is improved in adverse weather conditions	Accuracy	Performance degrades in weather conditions
[29]	Real-time Road Condition Detection via CNN	real time road monitoring	accurac	Requires pre-trained models, may not adapt quickly to new conditions
[30]	Assesses detection	mean average	Analysing the	It doesn't fully

	techniques in both clear and rainy conditions	precision (mAP)	effectiveness of object detection techniques that were tested and trained on visual data taken in both clear and rainy situations.	address these techniques' shortcomings in other unfavourable weather situations.
[31]	focuses on deep learning techniques for on-road vehicle detection and offers a useful collection of studies			Nevertheless, the study's narrow focus does not fully capture the variety of challenges AVs encounter in inclement weather.
[32]	contrasting YOLOv5, a one-stage detector, and Faster R-CNN, a two-stage detector, two well-known object detection models	mAP, recall, and training efficiency,	YOLOv5 performs better, especially as dataset size and image resolution rise. Faster R-CNN, on the other hand, does better in recognising small, far-off objects difficult lighting circumstances.	Hence requires hybrid model

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Table 5. *Comparison of Object Detection Approaches in Autonomous Vehicles using YOLO-NAS (Neural Architecture Search)*

Paper	Method	Performance Metrics	Outcome	Drawback
[33]	YOLO-NAS	High detection accuracy	Fast detection	operation constraints, significant GPU resource

Table 6. *Summary of Object Detection Approaches*

Paper	Matlab Box	Tool	YOLO	AWC	Deep Learning	YOLO-NAS
[9]	✓					
[10]	✓					
[11]			✓			
[12]			✓			
[13]			✓			
[14]			✓			
[15]			✓			
[16]			✓			
[17]				✓		
[19]				✓		
[20]				✓		
[21]				✓		

Paper	Matlab Tool Box	YOLO	AWC	Deep Learning	YOLO-NAS
[22]			✓		
[23]			✓		
[24]			✓		
[25]			✓		
[26]			✓		
[27]				✓	
[28]				✓	
[29]				✓	
[30]				✓	
[31]				✓	
[32]				✓	
[33]					✓

5. LIMITATIONS

Although enough experimental and theoretical research has been done on object detection techniques. But we need to do object detection and classification in suburban and rural areas. Although a variety of adverse weather circumstances are the main focus of our study, there may be additional environmental elements that were not thoroughly discussed in the reviewed literature, such as dust storms or dense fog. In [16] the proposed version of YOLOv5 show reduced performance in unfavourable weather circumstances, which frequently occur in realworld scenarios, is the main issue with the suggested technique. As a result, it lays the groundwork for future advancements in long-range object monitoring and severe weather. Further, predictive maintenance should be considered in object detection and classification. The real-time object detection and classification need to be performed very efficiently and accurately. We need to consider the parameters which can cause missed detection or wrong detection in object detection algorithms. In [9] although authors have recommended using a sensor fusion unit. Predictive maintenance can be adopted to continuously monitor proposed's system performance as prediction extension box is added in Yolo v5 [13]. Relative humidity also affects system's reliability [34]. In addition to considering the foggy conditions in [18], [22], relative humidity factor must be examined in object detection techniques. For conducting research under adverse weather conditions, quantitative fog measurements and sensors meteorological calibration is mandatory. In [26] the performance of YOLO has been adopted in sandy weather conditions using YOLO v5. The prediction box used in [13] in YOLO V5 can be adopted in the proposed model. The PM for cameras, LiDAR, radar, sensors need to be consider. The precision and reliability of AVs may be impacted in specific circumstances by the intrinsic limits of the detection algorithms included in our review, such as challenges in identifying small or obscured objects. Although they have limits, the YOLO models—such as YOLOv5, YOLOv7, and YOLOv8—perform exceptionally well in AV object detection. They are less accurate and more likely to provide false positives when faced with difficult circumstances like rain, fog, or low light. They also take a lot of computational power and difficulty in situations that are congested or occluded [15]. In [21] authors recommended to incorporate settings of congested and cluttered areas in adverse weather conditions in future.

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6. RECOMMENDATION

The following significant obstacles affect the effectiveness and dependability of autonomous car object detecting systems:

1. Real-Time Processing: Autonomous vehicles need algorithms that can process data quickly and accurately because they have to make decisions in a split second.
2. Adverse Weather: Rain, fog, and snow can impair sensor performance and increase the complexity of detection.
3. Urban Complexity: Crowded environments with overlapping objects demand advanced algorithms for differentiation and prioritization.
4. Error Minimization: Reducing false positives and negatives is essential for safety and reliability.

Further we have recommended to incorporate PM in object detection. Using a YOLO framework, predictive maintenance (PdM) and object detection are integrated through a multi-step process that uses the computer vision model to monitor asset conditions in real-time and initiate maintenance activities based on observed abnormalities or degradation.

6.1 Integration Techniques

1. In the overall framework, YOLO is used for data collection and preliminary analysis, followed by the use of other machine learning models for failure prediction and temporal analysis. Computer vision and machine learning components are usually integrated using a modular method.
2. Data Acquisition: Cameras are used to record highresolution video streams or photos (e.g., on drones for infrastructure inspection or fixed in a production setting). The main input is this visual data.
3. YOLO-Based Object Detection: A refined YOLO model (e.g., YOLOv5, YOLOv8) is fed the raw data. The model detects target objects in real time, such as electrical equipment, road surfaces, and wind turbine blades. It produces bounding boxes and confidence scores after locating and identifying abnormalities or flaws including wear, corrosion, cracks, or misalignments.
4. Feature Extraction for PdM: Over time, important characteristics pertaining to the state of the item are extracted rather than only producing a detection. These could include the number of faults found in a certain location, the size of a crack, or the shift in an object's position. Combining this data with other IoT sensor data, such as vibration or temperature, might enhance it.

7 CONCLUSION

In this paper, a detailed analysis on object detection techniques in autonomous vehicles is presented. We also included techniques in adverse weather conditions. According to our analysis, object detection in autonomous vehicles is challenging. Researchers need to work on realtime, highly accurate processing in complex urban environments, where adverse weather conditions can degrade sensor performance and minimizing detection errors is critical for safety and reliability. Further research can be conducted by incorporating predictive maintenance in object detection.

***Abbreviations**

The following abbreviations are used in this manuscript:

AoO Area of Overlap
AoU Area of Union
AV Autonomous vehicles
ADS Automated Driving Systems
FP False Positive
FN False Negative
ITS Intelligent Transport Systems
IoU Intersection over Union
IoT Internet of Things
LiDAR Light Detection and Ranging
PM Predictive Maintenance
TP True Positive
WHO World Health Organization YOLO You Only Look Once

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