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Advances in You Only Look Once (YOLO) algorithms for lane and object detection in autonomous vehicles

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A R T I C L E I N F O

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A B S T R A C T

Ensuring the safety and efficiency of Autonomous Vehicles (AVs) necessitates highly accurate perception, especially for lane detection and lane-change manoeuvres. Among object detection frameworks, "You Only Look Once" (YOLO) algorithms have emerged as prominent contenders due to their rapid inference and commendable accuracy. However, the broad spectrum of YOLO variants and their applications in complex, real-world environments remain insufficiently mapped, necessitating a more integrative and critical perspective than what is typically offered by surveys. This comprehensive review synthesizes theoretical foundations, architectural innovations, and empirical evaluations of YOLO-based algorithms in AV-related tasks. It not only highlights key findings—such as the notable gains in real-time detection and adaptability to a range of driving conditions—but also explicitly identifies persistent gaps and limitations. These include difficulties in detecting subtle or degraded lane markings, handling unpredictable environmental factors like adverse weather and varied lighting, mitigating adversarial perturbations, and scaling effectively across diverse datasets and geographic regions. By critically examining these vulnerabilities, we illuminate the opportunities for refining YOLO's training paradigms, optimizing model architectures, incorporating sensor fusion, and fostering universally applicable datasets. The implications of addressing these gaps extend beyond mere technical refinements. Proactively tackling YOLO's current challenges can expedite the realization of safer, more robust, and globally adaptable AV navigation systems. In doing so, this review provides clear, actionable insights for researchers, engineers, and policymakers, guiding them toward strategic innovations that will strengthen AV perception and contribute to more reliable, future-ready transportation solutions.

1. Introduction

Road safety is a critical global priority, as it not only saves lives and prevents injuries but also minimizes property damage, ensures smooth traffic flow, and reduces the social and economic costs associated with accidents (Khayyam et al., 2020). Recent technological advancements, particularly in self-driving cars or Autonomous Vehicles (AVs), have sparked significant interest as a potential solution to enhance road safety and revolutionize transportation systems (Fayyazi et al., 2023a). AVs are equipped to analyze their surroundings and make informed decisions to navigate roads safely with minimal or no human intervention. This technology offers several benefits, including reduced crash frequency and improved traffic efficiency (Kum Fai Yuen et al., 2020; Mola et al., 2022) listed in Table 5.

However, despite these advantages, substantial challenges remain. According to the World Health Organization (WHO), 1.35 million people lose their lives annually in vehicle collisions, with human error being the leading cause (Klaver, 2020). Contributing factors include excessive speeding, intoxicated driving, distractions such as mobile phone usage, and failure to use safety equipment like seat belts and helmets

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(Ming-Yuan Yu and Johnson-Roberson, 2019). AV technology holds the promise of mitigating such human-induced risks. Yet, challenges such as poor road conditions, complex topographies (e.g., sharp bends), severe weather, traffic congestion, accident liability concerns, and signal loss due to radar interference hinder widespread adoption. Among these, ensuring accurate and safe lane changes, a critical AV functionality, remains a significant hurdle. Failures in lane change systems have already resulted in severe accidents. For instance, in 2022, two fatal incidents involving Tesla's Autopilot system were attributed to failures in vision systems and object recognition (Greaser, 2022; Lambert, 2022). As the prevalence of AVs increases—projected to constitute three-quarters of all vehicles by 2040 (Newcomb, 2012)—addressing these challenges is imperative.

Lane changes, a core AV functionality, involve moving between lanes safely while avoiding collisions. This process requires effective lane detection, keeping within lane boundaries, and understanding lane characteristics. Despite advances in algorithms for lane keeping and detection, challenges persist, particularly in reliably identifying lanes under varying environmental conditions (Jian and Shi, 2020; Marzbani et al., 2019; Phan et al., 2020a; Milani et al., 2020; Zadeh et al., 2024). Robust object recognition systems are essential for maneuver planning, enabling AVs to detect stationary and moving objects, pedestrians, road signs, and lane markings (Hrag-Harouth Jebamikyous, 2022). Failures in object detection may lead to unsafe driving behavior, underscoring the need for continuous improvement in detection algorithms (Hrag-Harouth Jebamikyous, 2022; Ercan Avşar, 2022; Harisankar.R; Mehdi Masmoudi et al., 2019).

Numerous algorithms have been developed for object and lane detection, including Vanishing Point Guided Network (VPGNet) (L et al., 2017), Mask Region-Based Convolutional Neural Network (Mask RCNN) (H et al., 2018), Spatial Convolution Neural Network (SCNN) (P et al., 2017), Multi-Line Detection Conditional Random Fields model (MLD-CRF) (Hur et al., 2013), Boundary detection Network (RBNet) (Chen and Chen), LineNet (Dun Liang et al., 2020), and You Only Look Once (YOLO) (Jigang Tang and Liu, 2021). Among these, YOLO has emerged as a popular choice due to its exceptional speed and accuracy in real-time applications, particularly in AV systems (Peiyuan Jiang et al., 2021). Unlike traditional methods that rely on multi-stage pipelines, YOLO simplifies object detection by framing it as a single regression problem. This enables YOLO to predict bounding boxes and class probabilities in a single evaluation, achieving remarkable detection accuracy and speed.

Other networks, such as VPGNet and SCNN, support multitask detection, handling road classification, boundary detection, and vehicle recognition. However, multitask models often face performance tradeoffs due to the added computational complexity (Dun Liang et al., 2020). YOLO's ability to process images in real-time, coupled with its streamlined architecture, has made it a leading choice for AV applications (Peiyuan Jiang et al., 2021).

While significant progress has been made in detection and identification techniques, a notable gap remains in the objective comparison of different methodologies, particularly their robustness across real-world scenarios. Systematic evaluations and benchmarking of these techniques are needed to understand their strengths and limitations comprehensively. Such analyses will guide the development of more reliable detection methodologies tailored for AV applications.

This paper provides a comprehensive and critical examination of object detection algorithms and lane-change indices in the context of autonomous driving, placing special emphasis on the YOLO family of algorithms. By reviewing and synthesizing both theoretical frameworks and empirical performance outcomes—illustrated through comparisons on benchmark datasets like Karlsruhe Institute of Technology and Toyota Technological Institute (KITTI) and Common Objects in Context (COCO) - the study delineates YOLO's current strengths and pinpoint where its capabilities fall short. These identified gaps include challenges in reliably detecting subtle lane boundaries, adapting to varying environmental conditions, mitigating adversarial influences, and ensuring generalizability across diverse traffic scenarios. Beyond highlighting these issues, the paper discusses their broader implications for AV safety, efficiency, and scalability. It also proposes avenues for future work aimed at addressing the identified shortcomings. These suggestions, grounded in the observed limitations, may involve refining YOLO architectures to better handle complex roadway conditions, improving training and evaluation protocols to enhance robustness, or encouraging the development of standardized, representative datasets. By doing so, the paper contributes actionable insights that can guide subsequent research and development efforts toward more effective, reliable, and adaptable YOLO-based solutions for autonomous vehicles.

This paper is structured as follows: Section 2 describes the mathematical modeling and indices for lane changes and object detection. Section 3 reviews existing lane detection models. Section 4 provides a detailed discussion of the YOLO algorithm and its variants. Section 5 evaluates the applications and performance of YOLO variants. Section 6 highlights research challenges and future directions. Finally, Section 7 concludes the paper with key findings and recommendations.

1.1. Methodology

To ensure that this comprehensive review provides a thorough, unbiased, and methodologically sound analysis of YOLO algorithms in the context of lane and object detection for autonomous vehicles (AVs), a systematic search and selection process was employed. This process was designed to identify relevant literature spanning foundational theoretical contributions through to the latest advancements, ensuring both historical depth and contemporary relevance.

Search Strategy: The literature search was conducted across multiple reputable databases known for their coverage of computer vision, robotics, and transportation research, including IEEE Xplore, SpringerLink, ScienceDirect, and arXiv. The following keywords and Boolean combinations were used to ensure comprehensiveness and precision: "YOLO object detection," "autonomous vehicles," "lane detection," "deep learning in transportation," and "YOLO applications." These terms were chosen to capture the intersection of YOLO-based methodologies with AV-specific tasks, ensuring that works addressing either general YOLO improvements, specialized variants, or direct AV-related deployments were considered. To encompass both established foundational studies and recent innovations, the search timeframe ranged from 2006—capturing early influences on modern computer vision techniques—to 2024. This interval ensured the inclusion of seminal works that have informed current YOLO architectures, as well as the latest research reflecting state-of-the-art solutions and ongoing challenges in AV applications.

Selection Criteria: The initial screening involved reviewing titles, abstracts, and keywords to eliminate sources not directly relevant to YOLO algorithms in the AV context. Subsequently, a full-text review was performed on the remaining papers.

Inclusion Criteria:

- Studies that explicitly involve YOLO-based algorithms (original or variants) applied to lane detection, object recognition, or related perception tasks in AV environments.
- Works presenting empirical results (e.g., mean Average Precision [mAP], Frames Per Second [FPS], or accuracy metrics), comparative analyses, or detailed technical insights into YOLO's adaptation for AV scenarios.
- Peer-reviewed journal articles, conference proceedings, and reputable preprints in English, ensuring both academic rigor and accessibility.

Exclusion Criteria:

- Publications lacking empirical validation, technical detail, or direct relevance to YOLO and AV perception.
- Non-English sources or duplicates identified across multiple databases.
- Opinion articles, editorials, or short commentaries without methodological depth.

Through this filtration process, the focus remained on high-quality, substantively relevant sources. Table 1 illustrates how the collected literature was categorized according to specific application domains (e.g., lane detection, traffic monitoring, vehicle tracking), further ensuring a structured and contextually relevant data set.

Framework for Analysis: A conceptual framework guided the synthesis of selected studies to ensure that the review transcended a mere cataloging of methods:

1. Categorization by Domain and Task: Studies were grouped by their primary AV-related application (e.g., lane detection, object identification, adversarial robustness), enabling targeted comparative analysis of YOLO's performance across diverse yet thematically linked contexts.
2. Performance and Benchmarking: The analysis recorded key performance metrics and datasets commonly used in YOLO evaluations (e.g., KITTI, COCO). By comparing various YOLO iterations within consistent benchmarks, the review delineates improvements, persistent challenges, and context-specific strengths or weaknesses.
3. Architectural and Methodological Evolution: YOLO versions and custom variants were examined to identify patterns in architectural

Table 1
Categorization of research studies based on keywords and references related to YOLO applications in autonomous vehicles.

GROUPING	KEYWORDS	REFERENCES RETURNED
Object Detection for Autonomous Driving using YOLO	YOLO + Object Detection + Autonomous Driving	(Abhishek Sarda and Anupama Bhan), (Al-Saadi et al., 2022), (Mohanapriya et al.), (K and Nivetha), (Yingfeng Cai et al., 2021), (Yunfan Chen et al., 2022), (Zaghari et al., 2021), (Donghao Qiao, 2020), (Prithwish Sen and Sahu, 2022), (Jiwoong Choi et al.), (Aduen Benjumea et al., 2020), (Cheng Han et al., 2022), (Shen et al., 2023), (Jing J et al., 2020), (Jinjie Zhou et al., 2023), (Xu et al., 2023), (Cao et al., 2023), (Wibowo et al., 2023), (Diwan et al., 2023), (Chaudhry, 2024), (Ren et al., 2024), (Özcan et al., 2024), (Li et al., 2024), (Khan et al., 2024), (Bao and Gao, 2024)
YOLO-based Traffic Monitoring	YOLO + Traffic Monitoring	(Al-qaness et al., 2021), (Dewi et al., 2022), (Mistry and Degadwala), (Imanuel et al., 2024), (Flores-Calero et al., 2024), (Tang et al., 2024), (Kalva et al.), (Song et al., 2023), (Ali and Jalal), (Wang and Yu), (Sravanthi et al.), (Zhou et al., 2023), (Varshney et al.)
Energy Management for Autonomous Vehicles	Autonomous Vehicles + Energy management + Control	(Fayyazi et al., 2023b), (Phan et al., 2020b), (Zadeh et al., 2024), (Al-Saadi et al., 2022), (Phan et al., 2020b)
YOLO-based Vehicle Identification and Tracking for Autonomous Vehicles	YOLO + Vehicle Identification + Vehicle Tracking	(Azevedo and Santos), (Ercan Avşar, 2022), (Zhang et al.), (Chen et al., 2021), (Pandilwar and Kaur), (Prathap et al.), (Athish et al.), (Samsuri and Mohd Nazri), (Rani et al., 2024), (Soma et al.), (Naresh et al.), (Yass and Faris, 2023), (Farid et al., 2023)
Vehicle Speed Estimation with YOLO	YOLO + Speed Estimation + Autonomous Vehicles	(Asif Hummam Rais, 2021), (Rodríguez-Rangel et al., 2022), (Pandilwar and Kaur), (Do et al.), (Cvijetić et al.), (Peruničić et al.), (Vela et al.), (Soma et al.), (Lin et al., 2021), (Prajwal and Kumar), (Pemila et al., 2024), (Imanuel et al., 2024)
YOLO based algorithm in tackling adversarial perturbations in Autonomous vehicles.	YOLO + Autonomous Driving + adversarial perturbations	(Im Choi and Tian), (Jia et al., 2022), (Wu, 2024), (Jiang et al., 2023), (Li et al.), (Liang et al., 2024)
Object detection Algorithm	Object detection models + YOLO + Autonomous vehicles	(Hrag-Harouth Jebamikyous, 2022; Ercan Avşar, 2022; Harisankar.R; Mehdi Masmoudi et al., 2019), (L et al., 2017), (H et al., 2018), (P et al., 2017), (Hur et al., 2013), (Chen and Chen), (Dun Liang et al., 2020), (Mao et al., 2023), (Balasubramaniam and Pasricha, 2022), (Mahaur and Mishra, 2023), (Song et al., 2024), (Wang et al., 2024a), (Wang et al., 2024b), (Tahir et al., 2024), (Radha Pandey, 2021)
Lane detection Algorithm	Lane detection models + YOLO + Autonomous vehicle	(Lefevre et al., 2014), (Alin et al.), (Jigang Tang and Liu, 2021) (Huu et al., 2022), (Zakaria et al., 2023), (Jha et al., 2023), (Perumal et al., 2023), (Swain and Tripathy, 2024), (Öztürk et al., 2024), (Ji and Levinson, 2020), (Kim et al., 2008), (Mondschein et al., 2006), (Du et al., 2022), (Tu Zheng et al., 2022), (Yongqi Dong et al., 2021), (Lizhe Liu et al., 2021), (Tu Zheng et al., 2022), (Seokju Lee et al., 2017a), (Seokju Lee et al., 2017b), (Farzeen Munir et al., 2020), (Dong-Hee Paek and Wijaya, 2021), (Mohanapriya et al.; Phat Nguyen Huu and Tong Thi Quynh, 2022; Wei Yang et al., 2020; Xiang Zhang et al., 2018), (Edward Swarlat Dawam, 2020), (Dai et al., 2024), (Cao et al., 2024), (Liu et al., 2024)
YOLO algorithm and its application	YOLO + Application + Object detection	(Peiyuan Jiang et al., 2021), (J and Zhiqiang, 2017), (Zhiqiang and Jun), (Jiaqi Fan and Li), (Udaya Mouni Boppana et al., 2022), (Lecun et al., 1998), (Redmon and Farhadi, 2016), (Redmon and Farhadi, 2018), (Silva et al.), (Lu et al.), (Yang et al.), (Abhishek Sarda and Anupama Bhan; Yingfeng Cai et al., 2021; Kangkang Yang, 2022; Rui Wang et al., 2021), (Hussain and Finelli), (Solawetz, 2020), (Joseph Nelson, 2020), (L et al., 2022), (Wang et al.), (Zhiyang Zheng and Qin, 2023), (Chao Zhao et al., 2023), (Yulong Nan et al., 2023), (Huayi Zhou and Lu, 2023), (Xianchong Xu et al., 2023), (Lian et al., 2023), (Wei et al., 2023), (Wan et al., 2022), (Lee and Hwang, 2022), (G et al., 2021), (Ma et al.), (Ji and Zheng, 2021), (Mehdi Masmoudi et al., 2021), (Zillur Rahman and Ullah, 2020), (M and Ghantous, 2022; Kahlil Muchtar and Nasaruddin, 2020; Mario Gluhaković et al., 2020), (William Chin Wei Hung et al., 2022), (Liberios Vokorokos et al., 2020), (Deshpande and Herunde, 2020), (Irvine Valiant Fanthony et al., 2021), (Huibai Wang, 2020), (Wen Boyuan, 2020), (Shen Zheng et al., 2021), (Kim, 2019), (Geiger and Lenz, 2013). (B and PunithaMohana; Liu, 2022; Li et al., 2023; Yang et al., 2021; Lippi et al., 2021; Xiang et al., 2023; Li. et al., 2023; Dos Reis et al., 2019; Malta et al., 2021; Narejo et al., 2021; Zheng et al., 2022; Wang et al., 2023; Gündüz and Işık, 2023a; Gündüz and Işık, 2023b; Yang et al., 2023; Yu et al., 2018)
Road Safety and autonomous driving	Transportation + Safety + Autonomous driving	(Khayyam et al., 2020), (Fayyazi et al., 2023a), (Kum Fai Yuen et al., 2020; Mola et al., 2022), (Klaver, 2020), (Ming-Yuan Yu and Johnson-Roberson, 2019), (Greaser, 2022), (Lambert, 2022), (Newcomb, 2012), (Jian and Shi, 2020; Marzbani et al., 2019; Phan et al., 2020a; Milani et al., 2020), (Dagdeviren, 2018), (Teena Sharma et al., 2022)

enhancements, training procedures, and loss functions. This facilitated an understanding of how incremental modifications translate into improved performance for AV lane and object detection tasks.

4. Identifying Gaps, Limitations, and Future Directions: As a comprehensive review, the analysis went beyond summarizing current capabilities, highlighting unresolved issues such as handling subtle lane boundaries, coping with adverse weather or lighting conditions, resisting adversarial attacks, and addressing dataset limitations. Based on these findings, the paper proposes future research directions aimed at refining YOLO and guiding it toward more robust, reliable applications in AV systems.

Limitations of the Methodology: While the methodology was designed to be thorough and unbiased, certain limitations are acknowledged. Restricting the review to English-language publications may have excluded relevant non-English studies. Moreover, relying on established academic repositories may omit some emergent research from less prominent sources. Nevertheless, the outlined strategy ensures a systematically curated and analytically coherent body of literature, providing a solid foundation from which to understand YOLO's current position and potential trajectory in advancing autonomous vehicle perception.

2. Mathematical modelling for lane and object detection in autonomous driving

This section introduces a mathematical model and indices for lane changes and object detection, forming the foundation for accurate detection algorithms critical to safe lane-changing manoeuvres. Many existing solutions for autonomous lane changes and lane detection rely heavily on estimation methods, which often exhibit significant limitations, particularly in the context of AV safety. These methods are typically based on assumptions and approximations, leading to inaccuracies and unreliable outcomes. Furthermore, they frequently neglect key factors, such as dynamic vehicle behaviours and environmental variability, which are essential for precise detection and decision-making.

The effectiveness of AV systems heavily depends on the accuracy of their detection capabilities, as errors during lane changes can jeopardize safety. The coexistence of autonomous and human-driven vehicles adds complexity, requiring robust detection algorithms that can adapt to dynamic and unpredictable driving environments. Our research focuses on improving the reliability and performance of lane change and lane detection systems using YOLO algorithms, which are renowned for their real-time precision and resilience in handling complex, multi-object scenarios.

Reliable detection is pivotal to AV safety, particularly during lane changes. As shown in Fig. 1a and b, poor detection capabilities can lead to inaccurate estimations, increasing the risk of unsafe manoeuvres. This impact can be evaluated using safety and space payoff functions, which assess how detection accuracy affects vehicle interactions. The safety payoff (U_{Safety}) quantifies changes in the safety factor throughout the lane-changing process and is defined by Equation (1):

$$U_{Safety} = \frac{1}{2}\left(SP_{t=T_{cl}} - SP_{t=0}\right) \tag{1}$$

where $SP_{t=T_{cl}}$ is the safety factor at the end of the lane change, $SP_{t=0}$ is the initial safety factor, and T_{cl} is the time required to complete the manoeuvre (Yu et al., 2018). The safety factor at any given time t depends on the time headway ($T_{headway\ t}$) and a breakpoint (T_b), as expressed in the following equation:

$$SP_t = \begin{cases} 1 & T_{headway\ t} \le -T_b \\ \frac{2\left|T_{headway}\ \ t\right|}{T_b} - 1 & -T_b < T_{headway\ t} \le T_b \\ 0 & T_{headway\ t}\ > T_b \end{cases} \tag{2}$$

This piecewise function evaluates the safety factor as follows:

1. Unsafe Region ($T_{headway\ t} \le -T_b$): When the time headway is less than or equal to $-T_b$, the safety factor remains at 1, indicating unsafe conditions.
2. Critical Region ($-T_b < T_{headway\ t} \le T_b$): The safety factor decreases linearly with $\left|T_{headway}\ \ t\right|$, reflecting the increasing risk as the vehicles approach each other.
3. Safe Region ($T_{headway\ t}\ > T_b$, the safety factor remains at 1, signifying safe conditions.

The initial time headway between vehicles is given by:

$$T_{headway\ t=0} = \frac{P_1 - P_2}{V_2} \tag{3}$$

where P_i denotes the initial longitudinal position of vehicle i, and V_i represents its velocity. The time headway after T_{cl} seconds considers relative positions and adjusted velocities:

$$T_{headway\ t=T_{cl}} = \begin{cases} \frac{P_{1l} - P_{2l}}{v_2 + a_2 T_{cl}} & P_{1l} \ge P_{2l} \\ \frac{P_{2l} - P_{1l}}{v_1 + a_1 T_{cl}} & P_{1l} < P_{2l} \end{cases} \tag{4}$$

Here, P_{1l} and P_{2l} are the longitudinal positions of vehicles 1 and 2 after T_{cl} , calculated using:

$$P_{1l} = P_1 + v_1 T_{cl} + \frac{1}{2} a_1 T_{cl}^2 \tag{5}$$

$$P_{2l} = P_2 + v_2 T_{cl} + \frac{1}{2} a_2 T_{cl}^2 \tag{6}$$

where a_1 and a_2 are the accelerations of vehicles 1 and 2. These equations form the basis for evaluating the safety payoff during lane changes. The space payoff (U_{space}) measures changes in the space factor (RP) between vehicles:

$$U_{space} = \frac{1}{2}\left(RP_{t=T_{cl}} - RP_{t=0}\right) \tag{7}$$

where RP quantifies the spatial relationship between interacting vehicles (Yu et al., 2018). When two cars move in different lanes, the space factor (RP21_2) is defined as:

$$RP_{21\_2}(t) = \begin{cases} -1 & t_{21}(t) \le -3 \\ \frac{2}{3} t_{21}(t) + 1 & -3 < t_{21}(t) \le 0 \\ 1 & t_{21}(t) > 0 \end{cases} \tag{8}$$

where $t_{21}(t)$ is the time gap between vehicles, given by:

$$t_{21} = \begin{cases} \frac{P_2 - P_1}{v_2} & P_2 \le P_1 \\ \frac{P_2 - P_1}{v_1} & P_2 > P_1 \end{cases} \tag{9}$$

where P_i represents the initial longitudinal position of vehicle i relative to the road coordinate system, and v_i denotes its initial velocity. The time gap (t_{12}) between the vehicles is expressed as:

$$t_{12} = \frac{P_1 - P_2}{v_{following}} = -\frac{P_2 - P_1}{v_{following}} = -t_{21} \tag{10}$$

Here, $v_{following}$ is the velocity of the following vehicle. Since the total payoff function incorporates t_{12} for scenarios where the competing lane is occupied by Car 2, the relationship between the space factors of the interacting vehicles is defined as:

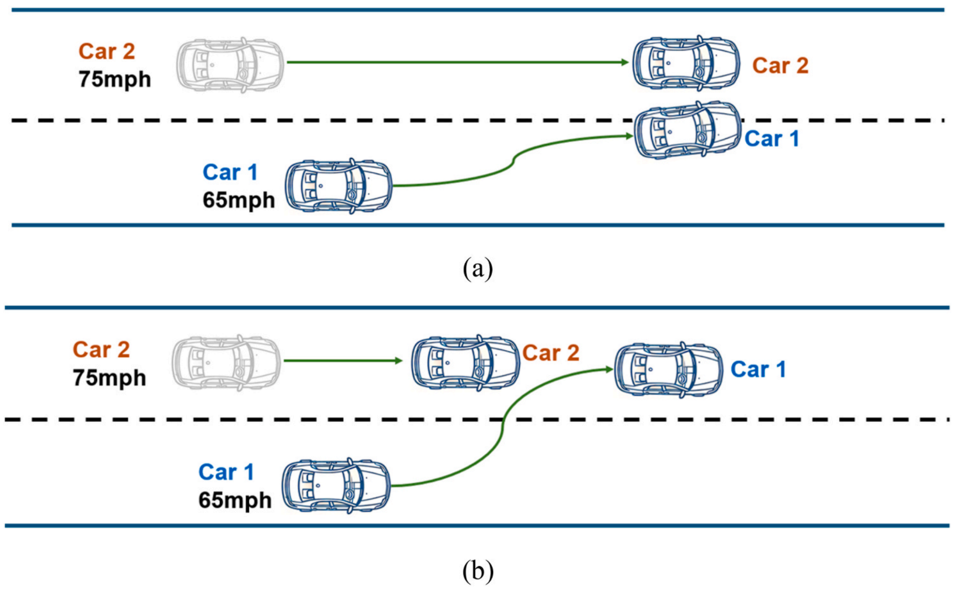


Fig. 1. Lane-changing scenarios: a) The competing vehicle hinders Car 2 from overtaking (aggressive competing vehicle). b) Car 1 strategically adjusts its position, enabling Car 2 to complete the overtaking manoeuvre safely and efficiently (Cautious competing vehicle). This figure is regenerated from Fig. 1 of reference (Yu et al., 2018).

$$RP_{12\_2}(t) = -RP_{21\_2}(t) \tag{11}$$

This relationship ensures that the space factor for one vehicle (RP_{12_2}) is the inverse of the other (RP_{21_2}), maintaining consistency in evaluating the spatial dynamics of vehicle interactions. When two cars move in the same lane, the space factor of Car 2 in the instant t is calculated by:

$$RP_{21\_2}(t) = \begin{cases} -1 & t_{21}(t) \leq -3 \\ \dfrac{t_{21}(t)}{3} & -3 < t_{21}(t) \leq 3 \\ 1 & t_{21}(t) > 3 \end{cases} \tag{12}$$

The total payoff function combines safety and space payoffs, weighted by the driver's aggressiveness (q):

$$U_{payoff} = f_w(a, a_0)\big((1-\beta(q))^* U_{safety}(a) + \beta(q)^* U_{space}(a) + 1\big) - 1, 0 \leq \beta(q) \leq 1 \tag{13}$$

Here, a represents the vehicle's future acceleration, while a_0 denotes its current acceleration. The parameter q captures the driver's aggressiveness and follows a Gaussian probability distribution N (0,1). The function f_w serves as a penalty term, accounting for abrupt changes in acceleration (i.e., jerk) and velocity, ensuring smoother transitions during manoeuvres. The payoff function incorporates two key components: U_{safety}, representing the safety payoff, and U_{space}, representing the space payoff. The weight of each component is determined by $\beta(q)$, the cumulative distribution function of q, which adjusts the balance between safety and space considerations. Specifically:

- $\beta(q)^* U_{space}$ quantifies the total space payoff.
- $((1-\beta(q))^* U_{safety}$ quantifies the total safety payoff.

The parameter $\beta(q)$ plays a critical role, as it determines the ratio between the space and safety payoffs, reflecting the trade-off between these two objectives. A higher $\beta(q)$ prioritizes spatial considerations, while a lower $\beta(q)$ emphasizes safety. This dynamic weighting mechanism allows the model to adapt to varying driving scenarios and driver behaviours.

Existing solutions and theories addressing autonomous lane changes and lane detection are predominantly estimation-based, yet these methods have inherent limitations that compromise their reliability and safety in critical applications like AV technology. Estimation methods rely on assumptions and approximations, which often lead to inaccuracies. Given the high stakes of AV operations, such inaccuracies cannot be tolerated. The complexity of autonomous lane changes and the quality of data used for estimation further exacerbate the problem, resulting in unreliable outcomes. This poses significant risks in scenarios requiring precise decisions, such as lane changes. Additionally, estimation methods are prone to biases stemming from the data or estimator, which may skew results and lead to suboptimal decision-making. Addressing these biases is essential to ensure accurate and safe manoeuvres.

Another drawback of estimation-based solutions is their opacity; they often involve intricate algorithms or models that are difficult to interpret. This lack of transparency hampers the validation and assessment of their reliability, making it challenging to detect and rectify potential errors or biases. Furthermore, such methods frequently overlook critical factors or variables that could significantly impact their performance, leading to incomplete or flawed conclusions. In the context of AVs, this limitation heightens safety risks during complex manoeuvres like lane changes.

The performance of lane-change manoeuvres in AVs is closely tied to two primary factors: detection accuracy and interaction with surrounding vehicles. Safety and space payoffs, critical components of lane-changing, depend on accurate detection. The safety factor hinges on identifying and localizing nearby vehicles, while the space factor, measured by the Relative Position (RP) value, determines a vehicle's ability to maintain a safe headway. A comparative analysis of detection techniques is crucial to address these challenges effectively.

Furthermore, the coexistence of autonomous and traditional human-driven vehicles on the road, as predicted for the foreseeable future (Dagdeviren, 2018), introduces additional unpredictability to traffic dynamics. This mixed-traffic environment amplifies the need for precise detection and reliable prediction capabilities. AVs must not only detect and communicate with other AVs using Vehicle-to-Vehicle (V2V) technologies but also anticipate the behaviour of non-autonomous vehicles (Khayyam et al., 2020; Al-Saadi et al., 2022; Phan et al., 2020b).

Object detection is pivotal in autonomous driving, ensuring the identification and localization of objects in dynamic environments to support safe navigation and decision-making. Mao et al. (2023)

provided a comprehensive review of three-dimensional object detection methodologies, highlighting the evolution from traditional Light Detection and Ranging (LiDAR)-based methods to advanced multimodal approaches integrating LiDAR, radar, and camera data for enhanced robustness. Complementing this, Balasubramaniam and Pasricha (2022) discussed ongoing challenges in object detection for AVs, such as computational complexity and the need for real-time performance, particularly under adverse weather conditions.

The detection of small objects, a critical requirement for identifying vulnerable road users like pedestrians and cyclists, has seen significant advancements. Mahaur and Mishra (2023) demonstrated improvements in small-object detection by enhancing YOLOv5, Fig. 2, while Wang et al. (2024a) proposed YOLOv8-QSD, optimized for small-object detection in complex road scenarios. Both studies underscore the importance of balancing detection accuracy and computational efficiency shown in Fig. 3.

Adverse weather conditions pose significant challenges to object detection models. Appiah and Mensah (2024) addressed this issue by integrating data augmentation and adversarial training techniques, enhancing robustness in challenging environments like fog and rain. Similarly, Tahir et al. reviewed traditional and deep learning approaches, emphasizing the necessity for advancements to maintain performance under extreme conditions. Wang et al. (2024b) illustrated the efficacy of YOLOv4 in urban object detection but noted the computational limitations for deployment on resource-constrained systems. Song et al. (2024) further highlighted the importance of robustness-aware training datasets and adversarial resilience to ensure reliability across diverse scenarios.

To overcome these challenges, advanced object detection algorithms have emerged as critical tools for enhancing AV safety and performance during lane-change manoeuvres. These algorithms, with their high accuracy, real-time perception capabilities, and robustness in complex scenarios, address major issues like variability, dynamic environments, and human driving behaviour. Addressing these challenges requires a synergistic approach combining robust sensor technologies, advanced machine learning techniques, and continuous adaptation to real-world conditions (Khayyam et al., 2020; Milani et al., 2020; Al-Saadi et al., 2022).

3. Overview of lane detection models for autonomous vehicles

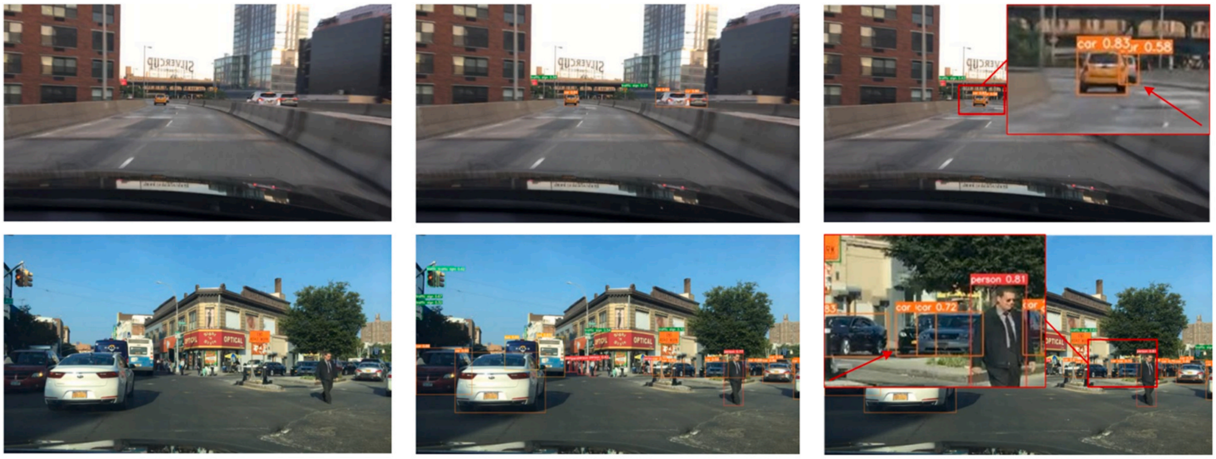
Accurate lane detection is an indispensable component of autonomous vehicle systems, ensuring precise navigation and safety in dynamic driving environments. Effective lane detection helps prevent potential dangers and accidents, playing a pivotal role in facilitating successful lane changes. Recent advancements have introduced a variety of approaches, ranging from traditional computer vision techniques to sophisticated deep learning models. This section synthesizes findings from notable studies on lane detection algorithms, emphasizing their methodologies, applications, and relevance to autonomous driving.

Huu et al. (2022) proposed a YOLO-based lane and obstacle detection algorithm, optimized for advanced network architectures in self-driving cars. This innovative method integrates real-time lane detection with obstacle avoidance, showcasing the adaptability and efficiency of YOLO in handling simultaneous tasks in dynamic scenarios. Similarly, Zakaria et al. (2023) conducted a systematic review of lane detection techniques, categorizing existing algorithms into traditional methods (e.g., Hough Transform and Canny Edge Detection) and modern approaches employing convolutional neural networks (CNNs). Their findings highlighted the superior accuracy of deep learning models in addressing complex lane geometries and challenging conditions, though computational costs remain a critical limitation for real-time deployment.

Jha et al. (2023) analysed lane and object detection methods, emphasizing the importance of integrating both functionalities for holistic autonomous driving systems. Their study underscored the real-time efficiency of YOLO-based models for lane detection but identified challenges in scenarios involving faded or occluded lane markings. Perumal et al. (2023) introduced LaneScanNET, a multi-task learning architecture designed for simultaneous lane and obstacle detection. This integrated approach reduced computational overhead while maintaining high accuracy, demonstrating its potential in resource-constrained settings.

Swain and Tripathy (2024) utilized YOLOv5's segmentation capabilities to develop a robust lane detection framework capable of handling complex road scenarios, including curves and intersections. Despite its strong performance, further optimization was noted to enhance adaptability to diverse environmental conditions. Öztürk et al. (2024) extended YOLOv5 to incorporate lane detection alongside vehicle, traffic sign, and pedestrian recognition, creating a

Fig. 2. Detection performance comparison in varying traffic environments: (a) YOLOv5 and (b) improved Scaled (iS)-YOLOv5. As traffic density increases from top to bottom, YOLOv5's prediction confidence decreases, leading to missed targets. In contrast, the proposed iS-YOLOv5 model maintains high confidence in detecting traffic signs and traffic lights, even in high-density traffic scenarios. This figure is regenerated from Fig. 8 of reference (Mahaur and Mishra, 2023).



Original image YOLOv8n YOLOv8n+Soft-NMS

Fig. 3. Comparison of detection results using three representative images. In these images, the vehicle in front is partially obscured by the vehicle behind it. When using the baseline YOLOv8n model, the front vehicle cannot be detected due to significant occlusion. However, with the application of Soft- Non-Maximum Suppression (NMS), the obscured vehicle is successfully detected, demonstrating improved detection performance under occlusion scenarios. This figure is regenerated from Fig. 11 of reference (Cao et al., 2024).

multi-functional framework for comprehensive traffic scene understanding. However, achieving consistent lane detection under adverse weather and lighting conditions remains a challenge.

In addition to lane detection, several theoretical frameworks support lane-changing decisions. These include Game Theory (Ji and Levinson, 2020), Gap Acceptance Theory (Kim et al., 2008), Cognitive Mapping Theory (Mondschein et al., 2006), and Lane Change Safety Index Theory (Du et al., 2022). While these theories provide valuable insights, their practical applications often depend on accurate and reliable lane detection systems.

Table 2 provides a detailed comparison of existing lane detection models, outlining their advantages and limitations. This comparative analysis highlights specific challenges such as computational costs, flexibility, robustness in complex scenarios, and sensitivity to occlusions or small lanes. YOLO-based models offer significant advantages, including real-time perception and adaptability to multi-object detection tasks. However, further research is required to leverage their potential fully.

Since the introduction of YOLO in 2015 (J and Zhiqiang, 2017), successive versions have evolved to address various object detection challenges, making YOLO a significant milestone in real-time vision-based algorithms. Table 3 outlines the timeline of YOLO development, showcasing the distinguished features and limitations of each version, from YOLOv1 to YOLOv11. The progression of YOLO demonstrates continuous improvements in detection accuracy, computational efficiency, robustness to occlusion, and adaptability to different environments. For instance, YOLOv5 introduced advanced features such as Cross Stage Partial (CSP)-Darknet-53 as a backbone, enhancing speed and accuracy for autonomous systems. More recent versions like YOLOv10 and YOLOv11 focus on lightweight models with gradient flow optimization and small-object detection capabilities, making them particularly suitable for real-time applications in resource-constrained settings listed in Table 4.

YOLO's ability to handle real-time object detection has made it a promising algorithm for autonomous vehicles (AVs). Its application spans diverse challenges, including severe weather conditions, low-light environments, occlusion handling (Ming-Yuan Yu and Johnson-Roberson, 2019), and intelligent traffic monitoring (Teena Sharma et al., 2022). The timeline illustrates how YOLO has adapted to meet the increasing demands of AV applications, addressing specific needs such as multi-object detection, improved localization, and better performance in cluttered or dynamic scenarios.

Peiyuan Jiang (Peiyuan Jiang et al., 2021) reviewed the progression of YOLO, emphasizing its advancements in feature extraction and target recognition, highlighting its role as a versatile and efficient detection system. While other studies, such as those by Radha Pandey (Radha Pandey, 2021) and Mehdi Masmoudi (Mehdi Masmoudi et al., 2019), evaluated object detection algorithms, they did not focus specifically on YOLO's real-time applications for AVs. Similarly, Udaya Mouni Boppana and Deivanayagampillai (Udaya Mouni Boppana et al., 2022) compared YOLO versions using distorted vehicle datasets, demonstrating their effectiveness under challenging conditions. Notably, YOLO has been shown to perform robustly under adverse conditions such as heavy rain or fog, where traditional methods often fail. However, existing research often overlooks YOLO's role in lane detection and lane-changing tasks, which are critical for the safety and functionality of AV systems.

This survey bridges that gap by focusing on YOLO's application in lane detection and manoeuvring. It identifies gaps in current methodologies, such as limited generalization across datasets and challenges in real-time adaptability for diverse driving environments. Furthermore, it highlights opportunities for future advancements, aiming to improve the reliability and safety of autonomous vehicles in complex driving scenarios. By exploring YOLO's potential in addressing these challenges, this review lays the groundwork for developing more advanced algorithms that integrate object detection with lane-detection tasks, ultimately enhancing AV performance and traffic safety.

4. Description of YOLO

Encouraged by the LeNet (Lecun et al., 1998) architecture for image classification, the original YOLO (version 1) architecture was developed as a Convolutional Neural Network (CNN) comprising 24 convolutional layers interspersed with max-pooling operations, followed by two fully connected layers at the end (Fig. 4). This architecture is designed around three main components: the Backbone, Neck, and Head. The Backbone represents the initial stage of the network, where convolutional layers are used to apply filters for preprocessing the input image. These layers progressively detect and process key features, starting from basic patterns like lines and edges to more complex geometries, ultimately enabling the identification of objects within the scene. The Neck serves as an intermediary layer, bridging the Backbone and the Head. It consists of fully connected feed-forward layers that aggregate and refine features extracted by the Backbone. This stage is critical for predicting object classification probabilities and proposing bounding boxes around

Table 2
Comparative analysis of lane detection models - datasets, advantages, and limitations.

STUDY	DATASET	MODEL TYPE	ADVANTAGES	DRAWBACK
Tu Zheng et al. (2022)	cuLANE	CLRNET (DLA-34)	Detect Lanes and improved localization accuracy	Fixed architecture limits flexibility; unsuitable for all applications; limited generalization.
Yongqi Dong et al. (2021)	TuSimple	SCNN_UNet_ConvLSTM2	Detect Lanes in challenging driving scenes	High computational cost and limited flexibility
Lizhe Liu et al. (2021)	CurveLanes	CondLaneNet-L (ResNet-101)	Detect lanes with complex topography	Designed specifically for lane detection; unsuitable for other tasks like vehicle or sign detection.
Tu Zheng et al. (2022)	LLAMAS	CLRNET (DLA-34)	Detect Lanes and improved localization accuracy	Fixed architecture limits flexibility; unsuitable for all applications; limited generalization.
Cheng Han et al. (2022)	BDD100K	YOLOPv2	Panoptic Driving Perception	High computational cost; struggles to detect small objects due to anchor-based design.
Seokju Lee et al. (2017a)	Caltech Lanes Washington	VPGNet	Detect and classify lanes and road markings	Relies heavily on accurate vanishing point detection, which is not always reliable in practice.
Farzeen Munir et al. (2020)	DET	LDNet	Lane detection and Localization in real-time performance	Limited ability to handle occlusion; struggles in complex urban environments.
Dong-Hee Paek and Wijaya (2021)	K-Lane	LLDN-GFC	Lane detection and real-time performance	High computational cost; limited ability to handle occlusion.
(Mohanapriya et al.; Phat Nguyen Huu and Tong Thi Quynh, 2022; Wei Yang et al., 2020; Xiang Zhang et al., 2018)	Custom Data	YoloV3	Lane and obstacle detection	Limited sensitivity to small lanes; struggles with complex urban environments.
Edward Swarlat Dawam (2020)	Custom Data	YoloV3	Smart city lane detection	Limited performance in complex environments.
Dai et al. (2024)	Custom Data	YoloV8	Lane detection using Hough Transformation	Computational complexity affects real-time performance.
Cao et al. (2024)	Custom Data	MSD-YOLO Improved YoloV8	Lane detection in crowded urban settings	Requires significant training time due to model complexity.
Liu et al. (2024)	Custom Data	DF-Yolo	Addresses the challenges posed by significant differences in target scales within complex scenes.	Generalization ability across datasets and driving conditions needs further validation.

detected objects. The Head, which is the final component, generates the network's output. It applies anchor boxes to the refined feature maps from the Neck and produces final output vectors that include class probabilities, objectness scores, and bounding box coordinates. This modular structure of YOLO allows flexibility, as the Head can be replaced or customized to adapt to specific tasks or datasets, demonstrating its versatility in various object detection applications.

4.1. Key processes in the YOLO algorithm

Fig. 4 provides an overview of the fundamental steps involved in the YOLO algorithm. The process begins with the division of the input image into an N × N grid of equally shaped cells. Each grid cell is assigned the responsibility of localizing and predicting the class of the object it overlaps with, along with a probability or confidence value for that prediction. Once the image is divided into grids, the algorithm employs Bounding Box Regression to determine bounding boxes, which are rectangular regions highlighting all the detected objects within the image. Since an image may contain multiple objects, YOLO uses a single regression module to extract the attributes of these bounding boxes in a unified manner.

To refine the results, Intersection over Union (IOU) is applied to filter and retain the relevant grid cells, ensuring precise localization of the detected objects. Non-Maximum Suppression is then used to eliminate redundant bounding boxes, retaining only those with the highest probability scores for each detected object. This approach ensures that the output is concise and efficient, providing accurate localization and classification.

The architecture of YOLO enables it to learn highly generalized features, allowing it to achieve superior detection speeds compared to other state-of-the-art detection methods, such as Region-Based Convolutional Neural Networks (R-CNN, Faster R-CNN, Mask R-CNN, and Granulated R-CNN) (Jiaqi Fan and Li). However, YOLO has certain limitations. The algorithm struggles with detecting small objects and distinguishing them when displayed in groups, such as a line of ants or densely packed items. Furthermore, YOLO's accuracy is generally lower compared to two-step object detection algorithms like Fast R-CNN, which use more elaborate mechanisms for classification and localization. Despite these limitations, YOLO remains a powerful and widely adopted algorithm for object detection due to its real-time performance and simplicity.

4.2. Performance metrics

Evaluating the performance of YOLO algorithms involves a comprehensive framework that relies on various performance metrics to assess their accuracy, localization capability, and computational efficiency. Among these metrics, Recall and mAP are the most critical for determining the model's effectiveness. Recall measures the model's ability to detect objects present in the input image, with values closer to 100 % indicating better detection performance. Precision evaluates the proportion of correct predictions among all predictions, with values ranging from 0 to 1, where higher values indicate fewer false detections and better accuracy.

The evaluation framework for YOLO algorithms often incorporates the 'true-false' and 'positive-negative' criteria, providing a structured approach to analyze detection performance. These criteria include True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN). A True Positive (TP) is recorded when the algorithm correctly detects an object, and the predicted bounding box overlaps with the ground truth box above a specified IoU threshold. False Positives occur when the algorithm incorrectly predicts a bounding box for a non-existent object or when the overlap with the ground truth box is below the IoU threshold. False Negatives represent cases where the

Table 3
Comparison of YOLO versions: Features and limitations of YOLOv1 to YOLOv11 for object detection and autonomous vehicle applications.

VERSION	FEATURES	LIMITATIONS
YOLOv1 (2015)	- Introduces Darknet framework and Leaky Rectify Unit (LReLU) with linear activation function. - Faster prediction than Fast R-CNN.	- High localization error. - Detects a maximum of two objects simultaneously. - Poor prediction accuracy for objects with aspect ratios not included in the training data.
YOLOv2 (2016)	- Introduces Darknet-19 as backbone. - Incorporates softmax, batch normalization, and anchor boxes.	- Not effective for small objects. - High rate of missed detections for distant objects.
YOLOv3 (2018)	- Introduces Darknet-53 as backbone and independent logistic classifiers. - Incorporates Feature Pyramid Network (FPN) and binary cross-entropy loss.	- Relatively low efficiency on larger-sized objects that run within the Darknet system.
YOLOv4 (2020)	- Uses CSPDarknet-53 as backbone, Spatial Pyramid Pooling (SPP), and PANet for feature aggregation. - Introduced "Bag of Freebies" and "Bag of Specials" for optimization.	- Slightly lower detection speed compared to YOLOv3. - High computational requirements.
YOLOv5 (2020)	- Employs Focus structure with CSPDarknet. - Auto-learns bounding boxes and improves loss calculations.	- Lower detection accuracy compared to YOLOv4.
YOLOv6 (2021)	- Incorporates efficient decoupled head with SIoU loss, EfficientRep backbone, and Rep-PAN. - Introduces anchor-free training and SimOTA tag assignment.	- Lacks pre-trained models for images larger than 640 pixels. - Limited types of pretrained models.
YOLOv7 (2022)	- Introduces de-coupled YOLO detection heads. - Improved inference speed and model accuracy.	- Poor detection accuracy in crowded scenes or for objects far from the camera.
YOLOv8 (2023)	- Employs a unified network encoding implicit and explicit knowledge for reference. - Suitable for multi-tasking and extendable for multi-modal learning.	- Poor performance for object detection in crowded scenes or distant objects.
YOLOv9 (2024)	- Incorporates anchor-free split ultralytics heads. - Improved loss function and better regularization techniques.	- Extensive use of convolutional blocks and C2f blocks increases computation and parameter count.
YOLOv10 (2024)	- Introduces Programmable Gradient Information (PGI) and GELAN (Gradient Enhanced Lightweight Architecture Network) for parameter utilization.	- Focuses on lightweight models that are under-parameterized, risking loss of information during the feedforward process.
YOLOv11 (2024)	- Introduces CPSA (Cross-Stage Partial with Self-Attention) and C3f2 to replace C2f blocks. - Enhanced accuracy for detecting small and occluded objects.	- Increased computational demands and larger model size limit deployment on devices with constrained resources.

algorithm fails to detect an object present in the ground truth, while True Negatives, though less relevant in object detection, indicate the correct absence of predictions in areas without objects.

Metrics such as precision and recall are derived from these criteria and are essential for evaluating object detection accuracy. Precision is calculated as shown in Equation (14):

$$Precision = \frac{TP}{TP + FP} \tag{14}$$

Similarly, recall is determined using Equation (15):

$$Recall = \frac{TP}{TP + FN} \tag{15}$$

The balance between precision and recall is often expressed through the F1-score, which combines these two metrics into a single value, allowing for a comprehensive evaluation of the algorithm's performance. Localization accuracy is another critical metric, assessed using IoU. IoU measures the overlap between predicted and ground truth bounding boxes, providing an indication of how accurately the algorithm localizes objects. The formula for IoU is provided in Equation (16):

$$IoU = \frac{Area\ of\ Overlap}{Area\ of\ Union} \tag{16}$$

Mean Average Precision further evaluates the algorithm's overall performance by calculating the average precision across all classes. It is defined as shown in Equation (17):

$$mAP = \frac{1}{n}\sum (Average\ Precision\ per\ class) \tag{17}$$

where n represents the total number of classes. Mean Average Precision is particularly useful for benchmarking object detection models, as it accounts for both precision and recall across all categories in the dataset.

Additional metrics, including Location Loss, Classification Loss, and Confidence Loss, provide further insights into the performance of YOLO. Location Loss evaluates the error in bounding box coordinates, while Classification Loss assesses the accuracy of predicted category labels for each detection. Confidence Loss measures the reliability of the predicted bounding boxes, accounting for the probability that each box contains a relevant object. Furthermore, Detection Time is critical for real-time applications, as it quantifies the time required for the algorithm to produce detection results, ensuring that it meets the stringent timing requirements of autonomous systems. Computational performance is often measured using Billion of Floating-Point Operations Per Second (BFLOPS) and Giga Floating Point Operations Per Second (GFLOPS), which indicate the number of floating-point operations executed per second, providing an understanding of hardware efficiency during algorithm deployment.

Although YOLO demonstrates exceptional real-time performance, it faces challenges such as accurately detecting small objects, distinguishing densely packed objects, and achieving the accuracy of multi-step object detection methods like Fast R-CNN. By focusing on these metrics, researchers can refine YOLO's performance, optimize parameters, and address its limitations. This ensures consistent benchmarking across datasets, facilitating meaningful comparisons and driving advancements in object detection, particularly in applications like autonomous driving.

4.3. Evolution and advancements of YOLO versions

Since its inception, YOLO has undergone significant development, with each version introducing innovations to enhance its performance, speed, and applicability in real-time object detection. Below is a detailed description of each YOLO version, emphasizing their distinct features, advancements, and limitations.

YOLOv2: It built upon the original model by introducing Darknet-19 as its backbone, which consisted of 19 convolutional layers. Batch normalization was implemented to stabilize training and improve convergence. The model used K-means clustering for anchor box generation, addressing the limitation of single object predictions per grid cell present in YOLOv1. YOLOv2 achieved a mAP of 78.60 % with an inference rate of 67 frames per second on the Pattern Analysis, Statistical Modelling, and Computational Learning Visual Object Classes (Pascal

Table 4
Comparative performance metrics of YOLO versions (YOLOv5 to YOLOv11).

YOLO Version	Params	FLOPs (G)	APval (%)	Latency (ms)	YOLO Version	Params	FLOPs (G)	APval (%)	Latency (ms)
YOLOv5-N	1.9	4.5	28.0	1.7	YOLOv8-N	3.2	8.7	37.3	6.16
YOLOv5-S	7.2	16.5	37.4	2.7	YOLOv8-S	11.2	28.6	44.9	7.07
YOLOv5-M	21.2	49.0	45.4	5.5	YOLOv8-M	25.9	78.9	50.6	9.50
YOLOv5-L	46.5	109.1	49.0	8.8	YOLOv8-L	43.7	165.2	52.9	12.39
YOLOv6-N	4.7	11.4	37.5	1.3	YOLOv8-X	68.2	257.8	53.9	16.86
YOLOv6-S	18.5	45.3	45.0	2.9	YOLOv9-N	2.0	7.7	38.3	6.0
YOLOv6-M	34.9	85.8	50.0	5.7	YOLOv9-S	7.2	26.8	46.8	6.5
YOLOv6-L	59.6	150.7	52.8	10.3	YOLOv9-M	20.1	76.7	51.4	8.0
YOLOv6-3.0-N	4.7	11.4	37.0	2.69	YOLOv9-L	25.5	102.6	53.0	9.0
YOLOv6-3.0-S	18.5	45.3	44.3	3.42	YOLOv9-X	58.1	189.4	55.6	11.5
YOLOv6-3.0-M	1.9	4.5	28.0	1.7	YOLOv10-N	2.3	6.7	39.5	1.84
YOLOv6-3.0-L	59.6	150.7	51.8	9.02	YOLOv10-S	7.2	21.6	46.8	2.49
Gold-YOLO-N	5.6	12.1	39.6	2.92	YOLOv10-M	15.4	59.1	51.3	4.74
Gold-YOLO-S	21.5	46.0	45.4	3.82	YOLOv10-L	24.4	120.3	53.4	7.28
Gold-YOLO-M	41.3	87.5	49.8	6.38	YOLOv10-X	29.5	160.4	54.4	10.70
Gold-YOLO-L	75.1	151.7	51.8	10.65	YOLOv11-N	2.6	6.5	39.5	1.5
YOLOv7-N	6.2	5.8	33.3	1.3	YOLOv11-S	9.4	21.5	47.0	2.5
YOLOv7-S	6.2	13.7	37.4	2.4	YOLOv11-M	20.1	68.0	51.5	4.7
YOLOv7-M	36.9	104.7	51.2	9.0	YOLOv11-L	25.3	86.9	53.4	6.2
YOLOv7-E6E	151.7	843.2	56.8	59.6	YOLOv11-X	56.9	194.9	54.7	11.3

Note: N – Nano for small and lightweight tasks, S – Small with improved accuracy, M – Medium for general-purpose use, L – Large for higher accuracy with higher computation, X – Extra-large for maximum accuracy and performance.

Table 5
Performance of YOLO-based algorithms: Overview of modified or customized methods built on baseline YOLO backbones, showcasing their parameters, FLOPs, mAP50 scores, FPS, and backbone architecture.

YOLO Version	Params	FLOPs (G)	mAP50 (%)	FPS	Backbone	Reference
KP-YOLO	–	–	–	–	YOLO adapted for QR codes	(Hussain and Finelli)
SSDA-YOLO	–	–	–	–	YOLOv5	Huayi Zhou and Lu (2023)
HD-YOLO	–	–	–	65	Fisheye optimized YOLO	(Wei et al., 2023)
MAD-YOLO	11.9	39.5	53.4	163.9	Improved YOLOv5	Xianchong Xu et al. (2023)
YOLO-AFC	–	–	54.25	15.1	YOLOv3	Lee and Hwang (2022)
YOLO-LRDD	19.8	17.4	57.6	86	YOLOv5s with Shuffle-ECANet	Wan et al. (2022)
YOLO-Compact	3.49	–	59.7	79	Simplified YOLO	(Lu et al.)
YOLOX	25.3	73.8	65.6	155	Adapted YOLOv3	G et al. (2021)
YOLOR	80.0	–	74.30	30	Unified network	(Azevedo and Santos)
YOLO-FD	–	–	75.2	34	Modified YOLOv3	(Silva et al.)
RDD-YOLO	N/A	–	81.1	57.8	Improved YOLOv5	Chao Zhao et al. (2023)
ORO-YOLO	7.5	–	82.8	38	Improved YOLOX	Lian et al. (2023)
YOLO-CIR	35.9	50.4	84.9	30	YOLOv5, ConvNeXt	Jinjie Zhou et al. (2023)
WGB-YOLO	50.9	–	86	34.6	Modified YOLOv3	Yulong Nan et al. (2023)
TS-YOLO	11.1	99.1	92.0	137	YOLOv4 with additional SPP	(Yang et al.)
YOLO-Cigarette	–	–	95.2	49	Improved YOLOv5	(Ma et al.)
YOLO-BYTE	–	–	97.3	47	YOLOv7 with ACmix	Zhiyang Zheng and Qin (2023)

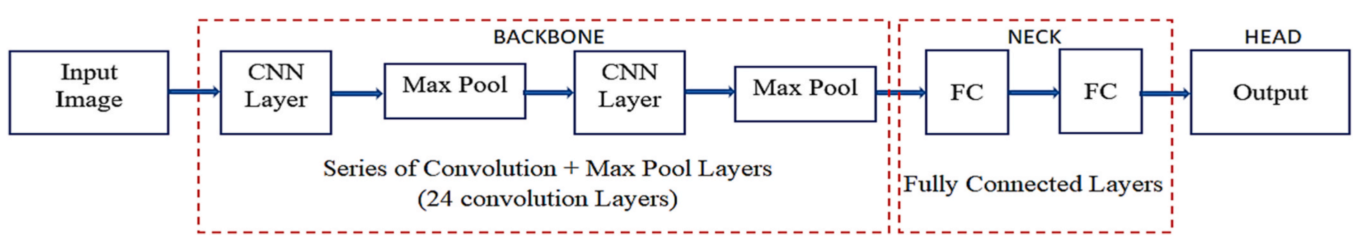


Fig. 4. Architecture of YOLO Version 1, illustrating the three main components—Backbone, Neck, and Head. The Backbone consists of a series of 24 convolutional layers interspersed with max-pooling layers for feature extraction. The Neck contains two fully connected layers for object classification and bounding box proposals, while the Head produces the final output, including class probabilities, objectness scores, and bounding box coordinates.

VOC) dataset (Redmon and Farhadi, 2016). While YOLOv2 performed well on large object detection, it struggled with small objects such as traffic lights due to limitations in feature extraction.

YOLOv3: It adopted Darknet-53 as its backbone (Redmon and Farhadi, 2018), a deeper and more robust architecture compared to Darknet-19. It introduced binary cross-entropy loss and an independent logistic classifier, replacing the SoftMax activation function used in YOLOv2. Additionally, YOLOv3 integrated a Feature Pyramid Network (FPN) for multi-scale detection, which improved the model's ability to detect small and overlapping objects. On the COCO dataset, YOLOv3 achieved a mAP of 44.3 % and an inference rate of 95.2 frames per second (Peiyuan Jiang et al., 2021). Despite its advancements, it exhibited relatively low performance on larger objects compared to its predecessors.

YOLOv4: It brought substantial improvements with CSPDarknet53 as its backbone and the addition of Spatial Pyramid Pooling (SPP) and

Path Aggregation Network (PANet) for enhanced feature fusion. It introduced innovative techniques like "Bag of Freebies" (data augmentation during training) and "Bag of Specials" (post-processing modules) to improve mapping accuracy and inference speed. On the COCO dataset, YOLOv4 achieved a mAP of 67.5 % with an inference rate of 62 frames per second. However, its larger model size and computational requirements made it less suitable for resource-constrained environments (Abhishek Sarda and Anupama Bhan; Yingfeng Cai et al., 2021; Kangkang Yang, 2022; Rui Wang et al., 2021).

YOLOv5: While not developed by the original YOLO authors, YOLOv5 introduced a Focus structure with CSPDarknet as its backbone. It emphasized ease of deployment and included auto-learning bounding box anchors for better adaptation to datasets. Despite an inference rate of 140 frames per second, YOLOv5's mAP of 56.40 % was lower than that of YOLOv4, highlighting trade-offs in accuracy for improved speed (Joseph Nelson, 2020).

YOLOv6: It introduced architectural enhancements with an Efficient Representation (EfficientRep) Backbone and a Re-parameterized Path Aggregation Network (Rep-PAN) Neck, optimized for hardware-friendly designs. Its decoupled head structure incorporated the Scaled Intersection over Union (SIoU) loss function, redefining penalty metrics for better regression accuracy (L et al., 2022). YOLOv6 achieved a mAP of 43.1 % and an inference rate of 520 frames per second. However, its applicability was limited to images no larger than 640 pixels, making it less versatile for larger datasets.

YOLOv7: It featured modular architecture with a Backbone (including Bottleneck Convolution (BConv), Efficient Layer Aggregation Network (ELAN), and Max Pooling Convolution (MPConv)), a Path Aggregation Feature Pyramid Network (PAFPN) as the Neck, and a Prediction head for confidence, category, and bounding box generation (Wang et al., 2022). This architecture efficiently fused multi-scale features, enabling YOLOv7 to achieve a balance between accuracy and speed, making it suitable for various object detection tasks.

YOLOv8: The latest addition to the YOLO series of real-time object detectors, was released in 2023 by Ultralytics [https://github.com/ultralytics/ultralytics]. It sets a new benchmark for accuracy and speed in object detection, building on the advancements of its predecessors. YOLOv8 introduces innovative features and optimizations, making it a versatile solution for a wide range of object detection tasks across various applications. The model incorporates advanced backbone and neck architectures, enhancing feature extraction and detection performance. Its anchor-free, split Ultralytics head improves accuracy and efficiency compared to traditional anchor-based methods. Striking an ideal balance between accuracy and speed, YOLOv8 is particularly suited for real-time object detection in diverse domains. YOLOv8 offers a range of pre-trained models tailored to specific tasks and performance requirements, simplifying model selection for users. The series includes specialized models for tasks such as object detection, instance segmentation, pose/keypoint detection, and classification. These models are individually optimized for high performance and accuracy and are compatible with multiple operational modes, including inference, validation, training, and export. This flexibility makes YOLOv8 adaptable to different stages of development and deployment.

YOLOv9: Released in 2024, YOLOv9 incorporated the Information Bottleneck Principle and Reversible Functions to improve data retention across layers, enhancing gradient stability and convergence (Wang et al.). Its novel Programmable Gradient Information (PGI) and Generalized Efficient Layer Aggregation Network (GELAN) optimized computational efficiency and accuracy, positioning YOLOv9 as a leading choice for real-time object detection.

YOLOv10: The architecture of YOLOv10 is designed to operate without NMS, employing consistent dual assignments to significantly reduce post-processing time and enhance overall latency. This is achieved through a lightweight classification head and various architectural optimizations that minimize computational redundancy. YOLOv10 demonstrates improved performance in the detection of small objects, particularly when employing a lower confidence threshold. The consistent dual assignment strategy enhances robust detection capabilities across diverse scenarios. Compared to YOLOv8, YOLOv10 excels in post-processing speed due to its innovative NMS-free approach, making it highly suitable for real-time applications where latency is a critical factor. In terms of detection accuracy, both models perform well; however, YOLOv10 exhibits a distinct advantage in handling small objects, especially with a lower confidence threshold. Furthermore, YOLOv10 efficiently optimizes its parameters, resulting in a model that is not only faster but also more compact than previous versions. YOLOv10 also introduces a scalable model framework tailored to specific tasks and performance requirements:

- N – Nano for small and lightweight tasks.
- S – Small upgrade of Nano with some extra accuracy.
- M – Medium for general-purpose use.
- L – Large for higher accuracy with higher computation.
- X – Extra-large for maximum accuracy and performance.

These scalable versions allow YOLOv10 to address a wide range of applications, from resource-constrained tasks to high-precision, computationally intensive operations.

YOLOv11: The latest iteration, integrated features from YOLOv9 and YOLOv10 to enhance speed and efficiency. It utilized multi-scale detection layers to ensure accurate identification of objects of varying sizes. YOLOv11 incorporated optimized non-maximum suppression techniques, achieving high detection accuracy while remaining computationally lightweight, making it versatile for diverse applications.

Each YOLO version represents a step forward in addressing challenges related to real-time object detection, including speed, accuracy, and adaptability. From its early iterations focused on large object detection to the latest anchor-free designs for small objects, YOLO has evolved to meet the demands of increasingly complex real-world scenarios, particularly in autonomous driving.

4.4. YOLO-based algorithms and custom variants

YOLOx: It introduces notable enhancements to the YOLO framework, establishing itself as a high-performance anchor-free detector. Leveraging recent advancements such as decoupled heads, an anchor-free approach, and an advanced label-assignment strategy, YOLOx achieves a superior balance between speed and accuracy. It builds upon the YOLOv3 architecture, ensuring extensive compatibility and adaptability across various sizes.

YOLO-BYTE: It improves the YOLOv7 backbone by incorporating a Self-Attention and Convolution mixed module (ACmix), enhancing feature extraction in complex scenarios. To reduce model complexity, it employs a lightweight Spatial Pyramid Pooling Cross Stage Partial Connections (SPPCSPC-L) module, optimizing performance while addressing missed and erroneous detections (Zhiyang Zheng and Qin, 2023).

RDD-YOLO: It is based on YOLOv5 and designed for fault detection. The model features Res2Net, Convolution, Batch Normalization, and SiLU (CBS), and Spatial Pyramid Pooling (SPP) blocks as its backbone and introduces a Decoupled Feature Pyramid Network (DFPN) as its neck. Using Complete Intersection over Union (CIoU) loss, it enhances the network's ability to detect and locate defects with precision (Chao Zhao et al., 2023).

YOLO-CIR: It combines YOLOv5 with ConvNeXt to optimize infrared object detection, effectively addressing challenges in low-visibility environments (Jinjie Zhou et al., 2023).

WGB-YOLO: It modifies YOLOv3 for multi-classification tasks using a wing feature-enhanced CSP backbone and a Bidirectional Feature Pyramid Network (Bi-FPN) head network. This architecture achieves balanced multiscale feature fusion, enhancing detection accuracy in agricultural settings (Yulong Nan et al., 2023).

SSDA-YOLO: It addresses domain adaptation challenges with a semi-supervised framework built on YOLOv5. By integrating knowledge distillation and consistency loss functions, Semi-Supervised Domain Adaptation (SSDA)-YOLO effectively adapts to cross-domain object detection tasks (Huayi Zhou and Lu, 2023).

MAD-YOLO: It optimizes YOLOv5 for underwater detection. Using Visual Object Vision (VOV) DarkNet as its backbone, the model enhances multiscale feature extraction to improve detection accuracy in aquatic environments (Xianchong Xu et al., 2023).

YOLO-Cigarette: It improves YOLOv5 by integrating a Fine-grained Spatial Pyramid Pooling (FSPP) module and a Multi-Spatial Attention Mechanism (MSAM), enhancing small-target detection capabilities (Xianchong Xu et al., 2023).

ORO-YOLO: It enhances YOLOX for on-road object detection by using a reparameterization method and a feature enhancement module. This design improves performance in detecting complex road environments (Lian et al., 2023).

HD-YOLO: It addresses fisheye distortion issues by incorporating a radius-aware loss function and a channel attention module, making it highly effective for head detection tasks in distorted images (Wei et al., 2023).

YOLOR: It uses a unified network that encodes implicit and explicit knowledge, excelling in multi-task learning. With a mAP of 74.3 and an inference rate of 30 FPS on the COCO dataset, it offers fast and reliable performance for multi-modal learning tasks.

YOLOX: It is an anchor-free algorithm that uses decoupled detection heads. By separating classification and regression tasks, YOLOX enhances computation cost efficiency, convergence speed, and model accuracy. On the COCO dataset, it achieves a mAP of 51.20 % and an inference rate of 57.8 FPS.

YOLO-LRDD: It modifies YOLOv5s with Shuffle-Efficient Channel Attention Network (ECANet) as its backbone and BiFPN for robust feature aggregation. This configuration improves the network's ability to describe features and enhances reliability (Wan et al., 2022).

YOLO-AFC: It introduces adaptive frame control to address real-time processing challenges in network camera environments. YOLO-AFC minimizes service delays while maintaining high precision and ease of use (Lee and Hwang, 2022).

YOLO-FD: It modifies YOLOv3 to specialize in face detection, achieving real-time detection for faces as small as 16 pixels at 34 FPS (Silva et al.).

YOLO-Compact: It is designed for single-category detection, optimizing the YOLO framework for lightweight and efficient applications (Lu et al.).

TS-YOLO: It improves YOLOv4 by adding two additional SPP modules, enhancing accuracy and increasing the number of detected objects (Yang et al.).

KP-YOLO: It modifies the YOLO algorithm to detect feature points in single-class settings, such as QR code detection (Hussain and Finelli).

WOG-YOLO: Xu et al. (2023) introduced this model, which integrates a weighted optimization graph with YOLO. It improves detection accuracy and speed in complex road environments.

MCS-YOLO: Cao et al. (2023) developed this multiscale detection algorithm for recognizing diverse objects in cluttered road environments. It enhances recognition by leveraging multiscale features.

YED-YOLO: Bao and Gao (2024) introduced this algorithm, focusing on energy-distribution-based improvements to enhance YOLO's detection accuracy and robustness in autonomous driving systems.

5. Applications and performance analysis of YOLO variants in object detection

In this section, we explore the diverse applications of YOLO algorithms in object detection, highlighting their practical utility across various domains. A comparative analysis is then conducted to evaluate the performance of different YOLO variants using two widely recognized benchmark datasets: COCO and KITTI. These datasets are extensively used for object detection tasks due to their comprehensive annotations and relevance to real-world scenarios. The evaluation focuses on key performance metrics, including accuracy, precision, and detection time, providing a detailed understanding of the capabilities and limitations of each YOLO variant.

5.1. Applications of YOLO variants in autonomous driving

Numerous variants of the YOLO algorithm have been developed, each with unique features, strengths, and limitations. This study surveys and summarizes previous works that leverage YOLO variants for applications focused on lane detection and autonomous driving. However, not all methods, especially those involving lane change manoeuvres, are relevant to similar applications. Limited studies specifically address YOLO applications for autonomous lane changes and manoeuvres. Some research has categorized vision-based lane detection into two-step and one-step methods (Jigang Tang and Liu, 2021), while Peiyuan Jiang (Peiyuan Jiang et al., 2021) highlighted differences and similarities between YOLO versions and other CNNs.

YOLOv3 remains one of the most widely utilized versions in AVs. Studies by Phat Nguyen Huu (Phat Nguyen Huu and Tong Thi Quynh, 2022), Mohanapriya (Mohanapriya et al.), Wei Yang (Wei Yang et al., 2020), Xiang Zhang (Xiang Zhang et al., 2018), and Zheng (Ji and Zheng, 2021) applied YOLOv3 to detect lanes and obstacles with high mAP. These works demonstrated improvements in detection accuracy and real-time performance by adjusting network layers and detection scales, though they often overlooked brightness variation effects on detection accuracy. Edward Swarlat Dawam (Edward Swarlat Dawam, 2020) trained YOLOv3 with over 25,000 images to robustly detect 25 road surface marking classes, while Mehdi Masmoudi (Mehdi Masmoudi et al., 2021) applied YOLOv3 in an end-to-end vehicle-following framework to identify leading vehicles and obstacles. Zillur Rahman (Zillur Rahman and Ullah, 2020) employed YOLOv3 to detect vehicles traveling the wrong way under various weather and lighting conditions.

YOLOv3 also excels in real-time localization for collision avoidance. Its applications include subclass traffic sign detection (M and Ghantous, 2022; Kahlil Muchtar and Nasaruddin, 2020; Mario Gluhaković et al., 2020), extreme weather vehicle detection (Udaya Mouni Boppana et al., 2022), and highway vehicle tracking (Kahlil Muchtar and Nasaruddin, 2020; William Chin Wei Hung et al., 2022). Liberios Vokorokos (Liberios Vokorokos et al., 2020) demonstrated YOLOv3's capacity for limited colour detection, suggesting enhancement with histograms and advanced image recognition techniques. While YOLOv3 offers superior frame processing speed, studies note its limitations in computational complexity and processing memory demands (Mehdi Masmoudi et al., 2019; Deshpande and Herunde, 2020).

YOLOv4 introduced architectural enhancements, making it suitable for diverse AV applications. Irvine Valiant Fanthony (Irvine Valiant Fanthony et al., 2021) identified Tiny YOLOv4 as highly compatible with real-time object detection for electric AVs, while Huibai Wang (Huibai Wang, 2020) and Ghantous (M and Ghantous, 2022) employed it for traffic light detection and classification, achieving distance estimation but relying on dataset robustness. Ercan Avşar (Ercan Avşar, 2022) recommended YOLOv4 for detecting, counting, and tracking vehicles in roundabout videos, while Wen Boyuan (Wen Boyuan, 2020) applied it to pedestrian detection with favourable results. Donghao Qiao (Donghao Qiao, 2020) compared YOLOv4 and Faster R-CNN, finding YOLOv4 superior in speed and accuracy (68 fps). Asif Hummam Rais (Asif Hummam Rais, 2021) integrated YOLOv4 with Kalman filters for vehicle speed estimation in video streams, addressing class distinction issues. Dewi et al. (2022) applied SPP to enhance YOLOv4 for feature extraction, achieving state-of-the-art mAP and BFLOPS metrics.

Challenges persist in enhancing YOLO-based autonomous lane detection. High computational costs, limited dataset generalization, and inference rate complications hinder advancements without sacrificing accuracy. Phat Nguyen Huu (Phat Nguyen Huu and Tong Thi Quynh, 2022) suggested exploring semi-supervised learning, meta-learning, and neural architecture search to improve detection. While YOLOv3 offers robust performance, its complexity necessitates research toward lightweight, accurate models like YOLOv4. Although some studies claim Support Vector Machines (SVMs) outperform YOLO in accuracy, YOLO's speed advantage often makes it the preferred choice for AVs (Mehdi Masmoudi et al., 2021).

Detection rates improve significantly with YOLOv5, as Teena Sharma (Teena Sharma et al., 2022) demonstrated by training it on diverse datasets for car, traffic light, and pedestrian detection in various weather conditions. Studies also revealed that modifying YOLOv5's anchors and structural elements enabled better detection of larger, blurred, or smaller objects without compromising inference time (Yunfan Chen et al., 2022; Prithwish Sen and Sahu, 2022; Aduen Benjumea et al., 2020; Shen Zheng et al., 2021). Wibowo et al. (2023) enhanced YOLO for dense urban traffic, focusing on crowded condition detection. Chaudhry (2024) introduced SD-YOLO- Adaptive Weighted Dense Network (AWDNet), a hybrid approach to tackle adverse weather detection challenges, while Ren et al. (2024) developed Dilated Convolutional Weighting (DCW)-YOLO with dynamic convolutional weighting for diverse road scenarios.

Recent advancements include Özcan et al.'s (Özcan et al., 2024) metaheuristic-optimized YOLO for adverse weather and Li et al.'s (Li et al., 2024) YOLO- Adaptive Lightweight Precision Hybrid Architecture (ALPHA), emphasizing precision and efficiency for real-time applications. Khan et al. (2024) applied YOLO to pothole detection, achieving practical results for poorly maintained roads. These advancements highlight YOLO's versatility and ongoing relevance in addressing AV challenges.

5.1.1. Advancements in YOLO-based traffic monitoring systems

YOLO-based algorithms have emerged as a cornerstone for traffic monitoring systems due to their ability to perform real-time object detection with high accuracy and efficiency. These algorithms have applications spanning various domains of intelligent transportation, including vehicle recognition, traffic sign detection, signal optimization, and monitoring complex traffic environments. Recent advancements in YOLO-based methods have aimed to enhance their performance in diverse and challenging scenarios, such as urban mixed traffic, adverse weather conditions, and large-scale aerial monitoring.

Imanuel et al. (2024) provide a comprehensive review of YOLO's evolution and its implementation across different domains, emphasizing its real-time performance, high detection accuracy, and adaptability to various applications. Mistry and Degadwala (Mistry and Degadwala) proposed a customized YOLO framework tailored to improve multi-type vehicle recognition. Their approach yielded significant improvements in precision and recall, surpassing standard YOLO models. Similarly, Song et al. (2023) introduced Multi-scale Efficient Backbone (MEB)-YOLO, optimized for detecting vehicles in complex traffic scenarios by addressing occlusion and vehicle overlap, which are common challenges in urban environments.

Flores-Calero et al. (2024) systematically reviewed traffic sign detection and recognition using YOLO, highlighting the algorithm's adaptability to varying lighting and weather conditions. They demonstrated the potential of advanced pre-processing techniques to detect less distinct traffic signs. Wang and Yu (Wang and Yu) enhanced YOLOv4's feature extraction capabilities for improved detection in challenging visual environments. In intelligent traffic systems, Kalva et al. (Kalva et al.) developed a scalable, real-time monitoring system by integrating YOLO with deep learning techniques for urban applications. Sravanthi et al. (Sravanthi et al.) utilized YOLOv8 to dynamically control traffic signal durations based on real-time vehicle detection, showcasing its potential for optimizing traffic flow.

For aerial imagery applications, Ali and Jalal (Ali and Jalal) employed YOLO for vehicle detection and tracking, integrating centroid tracking for continuity in dynamic settings. Zhou et al. (2023) tailored YOLO for urban mixed traffic, enhancing its capabilities to detect diverse participants like bicycles and pedestrians. Tang et al. (2024) introduced YOLO-Fusion, integrating YOLO with IoT frameworks for advanced detection in smart transportation systems. This method demonstrated enhanced performance in complex traffic environments by combining sensor and visual inputs. Varshney et al. (Varshney et al.) extended YOLOv8 for long-distance video streaming detection, providing scalable solutions for intelligent traffic monitoring.

Challenges in YOLO-based traffic monitoring primarily arise from environmental conditions, computational demands, and dataset limitations. Factors like adverse weather, occlusions, and overlapping objects impact detection accuracy, while high computational requirements hinder real-time performance on resource-constrained devices. Limited datasets restrict generalization across varied traffic scenarios, affecting performance in settings such as rural roads and highways. Addressing diverse traffic participants like cyclists and pedestrians in mixed traffic remains an ongoing challenge. Moreover, adversarial vulnerabilities and integration issues with IoT frameworks underscore the need for robust, scalable, and secure solutions to advance YOLO-based traffic monitoring systems.

5.1.2. Addressing adversarial vulnerabilities in YOLO-based autonomous vehicle systems

Adversarial perturbations present a significant challenge to the reliability and accuracy of YOLO-based object detection systems in autonomous vehicles. These subtle, often imperceptible modifications can deceive detection models, causing errors in object recognition and jeopardizing decision-making processes. This section examines the vulnerabilities of YOLO detectors to adversarial attacks and reviews the defensive strategies developed to mitigate these risks.

Choi and Tian (Im Choi and Tian) highlighted the susceptibility of YOLO-based systems to adversarial attacks, including both digital and physical adversarial examples. Their analysis demonstrated that such attacks could lead to misclassification or complete evasion of objects, undermining the reliability of perception systems in autonomous vehicles. Similarly, Wu (2024) explored practical adversarial attack strategies, emphasizing the challenges of detecting and mitigating such attacks in real-world scenarios.

Jia et al. (2022) conducted experiments on traffic sign recognition systems to demonstrate how physical adversarial examples, such as stickers or camouflage, could manipulate YOLO-based models. These perturbations were effective under varying lighting and environmental conditions, underscoring the need for robust defence mechanisms. Jiang et al. (2023) extended this research by evaluating the physical-world robustness of YOLO detectors for vehicle detection. They introduced simulation environments to test adversarial examples and proposed enhancements to YOLO's training pipeline to improve robustness.

Defensive strategies against adversarial perturbations have also been explored. Liang et al. (2024) investigated adversarial patch attacks and proposed mechanisms such as adversarial training and patch-based shielding techniques. Their findings demonstrated that integrating these defences significantly improved YOLO's reliability in dynamic driving environments. Li et al. (Li et al.) proposed a simulation-based framework for detecting object-evasion attacks on YOLO detectors. By integrating adversarial detection mechanisms into the YOLO pipeline, their method effectively identified and mitigated evasive adversarial objects, improving detection accuracy in autonomous driving contexts.

Despite advancements in addressing adversarial vulnerabilities, challenges remain. YOLO-based algorithms must balance computational efficiency with robustness against adversarial attacks. Future research should focus on integrating adversarial training, simulation-based defences, and real-world validations to enhance YOLO models' ability to operate reliably in adversarial environments. Additionally, efforts should be directed toward improving the detection of physical adversarial examples and developing proactive defence mechanisms that can adapt to evolving threats.

By addressing these challenges, YOLO-based systems can be made more resilient, ensuring the safety and reliability of autonomous vehicle operations in complex and adversarial scenarios.

5.1.3. YOLO-based vehicle identification, speed estimation and tracking algorithm for autonomous vehicles

Vehicle identification, speed estimation, and tracking are pivotal components in the development of autonomous vehicle systems, ensuring safe navigation and compliance with traffic regulations. YOLO-based algorithms have emerged as a powerful tool in these applications due to their real-time object detection and tracking capabilities. This section reviews recent advancements in YOLO-based techniques for these tasks.

YOLO's high accuracy and speed have significantly advanced vehicle identification. Farid et al. (2023) proposed a YOLO-based detection method optimized for unconstrained environments, demonstrating the algorithm's ability to accurately detect vehicles in diverse scenarios. Similarly, Pemila et al. (2024) combined YOLO with machine learning classifiers to achieve real-time vehicle classification across extensive datasets, addressing the complexities of mixed traffic. Rani et al. (2024) introduced Lightweight Vision (LV)-YOLO, a system that integrates vehicle detection with logistic speed estimation and counting, showcasing YOLO's versatility in multi-task scenarios.

Accurate speed estimation is essential for collision avoidance and traffic management. Do et al. (Do et al.) presented an algorithm for estimating the speed of fast-moving vehicles in intelligent transportation systems, achieving high accuracy by integrating YOLO with advanced data processing techniques. Cvijetić et al. (Cvijetić et al.) combined YOLO with a 1D convolutional neural network (1D-CNN) for vehicle speed estimation, demonstrating its efficacy in real-time applications. Lin et al. (2021) developed a system using virtual detection zones and YOLO to simultaneously count, classify, and estimate vehicle speeds, underlining its potential in urban traffic monitoring.

YOLO-based algorithms have shown considerable promise in vehicle tracking applications. Samsuri and Nazri (Samsuri and Mohd Nazri) developed a deep learning-based visual tracking system for traffic flow monitoring, highlighting YOLO's effectiveness in real-time surveillance. Soma et al. (Soma et al.) employed YOLOv8 for real-time vehicle tracking and speed estimation, emphasizing the efficiency of advanced YOLO iterations in handling dynamic traffic environments. Yass and Faris (2023) reviewed YOLO-based techniques for tracking vehicles and addressing wrong-way driving scenarios, demonstrating YOLO's critical role in enhancing road safety through reliable tracking systems.

Several studies have explored multi-modal approaches that integrate vehicle tracking and speed estimation. Prajwal et al. (Prajwal and Kumar) proposed a multi-vehicle tracking model using deep learning, demonstrating scalability across multiple vehicle types and speeds. Prathap et al. (Prathap et al.) highlighted advancements in tracking systems by combining YOLO for object detection with additional layers for speed prediction, illustrating the adaptability of YOLO frameworks in complex traffic scenarios.

Despite the successes of YOLO-based algorithms, challenges persist. Chen et al. (2021) observed that variations in video resolution and UAV altitude affect tracking accuracy, necessitating adaptive models. Similarly, Vela et al. (Vela et al.) emphasized the importance of lightweight models to ensure computational efficiency in urban scenarios. Future research must focus on improving model robustness, integrating multi-modal data, and optimizing YOLO frameworks to operate effectively in resource-constrained environments. Addressing these challenges will further enhance YOLO's applications in vehicle identification, speed estimation, and tracking, solidifying its role in autonomous vehicle systems.

5.2. Case studies: YOLO variants in object detection

Two widely used datasets for evaluating YOLO algorithms are COCO and KITTI. The COCO dataset is a large-scale benchmark designed for object detection, segmentation, and captioning. It includes a diverse collection of images with detailed object annotations, making it ideal for training and evaluating object detection models (Kim, 2019). In contrast, the KITTI dataset focuses on autonomous driving and computer vision tasks. It features high-resolution images annotated for object detection and tracking, making it particularly suitable for applications related to self-driving vehicles (Geiger and Lenz, 2013).

The performance of YOLO algorithms depends significantly on the datasets used for evaluation, as there is no single unified dataset for benchmarking. As a result, algorithm performance must be assessed in the context of the dataset employed in each study.

This section examines six YOLO models applied to object detection tasks using the COCO and KITTI datasets. Both datasets are popular benchmarks in this domain, enabling researchers to evaluate and compare algorithm performance.

For the COCO dataset, as illustrated in Fig. 5, YOLOv11 demonstrates the highest accuracy and precision, followed closely by YOLOv10 and YOLOv9. These models show considerable improvements in both metrics compared to earlier YOLO iterations, reflecting advancements in feature extraction and detection algorithms. Similarly, on the KITTI dataset, as shown in Fig. 6, YOLOv11 again achieves superior performance, with YOLOv10 and YOLOv9 maintaining their strong performance in accuracy and precision.

While YOLOv11, YOLOv10, and YOLOv9 lead in terms of detection performance, other YOLO versions also perform acceptably across various object detection tasks. Incremental improvements in precision and accuracy are observed in newer YOLO variants, underlining the ongoing enhancements in the algorithm's architecture and capabilities.

6. Challenges in advancing YOLO for lane detection and manoeuvres in AVs

Advancing YOLO's application for lane change detection and manoeuvres in AVs requires addressing several pressing challenges. Despite the significant progress in YOLO-based methodologies, there are areas that demand focused research to enhance their adaptability, accuracy, and robustness. The following challenges outline the key areas for improvement:

1. **Adaptability to Diverse Driving Conditions:** YOLO algorithms, while effective, need further optimization to handle a wide range of variabilities in vehicle environments, including irregular lane shapes, inconsistent line quality, and interactions with other road users. A comprehensive comparative study of YOLO variants, such as YOLOv4, YOLOv6, and YOLOv7, under varying driving conditions is essential. Research should include tuning hyperparameters to identify and manage extreme cases. Hybridizing architectures of these YOLO versions can improve detection and classification in dynamic AV environments, particularly for different traffic and road conditions.
2. **Enhancing Lane Detection Accuracy:** Improving YOLO-based lane detection algorithms in complex scenarios remains a priority. Accurate detection requires robust handling of irregular spatial relationships and occlusions. Enhancements in training methodologies, such as employing larger datasets of labelled images, are necessary. Transitioning to advanced YOLO versions like YOLOv6 and YOLOv7, rather than relying on older models like YOLOv3, could yield better performance. Additionally, implementing a scoring metric to detect potential misclassifications in AV perception algorithms can help ensure error-free decision-making in critical real-world scenarios.
3. **Optimization of YOLOv8 for Lane Detection:** Focused research on the YOLOv8 architecture is crucial to further refine its algorithm for

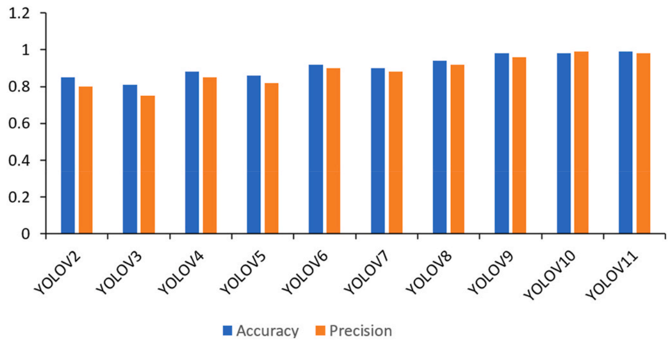


Fig. 5. Comparison of accuracy and precision across different YOLO versions evaluated on the COCO dataset.

enhanced lane detection. This includes optimizing key parameters and training procedures to improve its accuracy and efficiency. By fine-tuning these aspects, researchers can push YOLOv8's performance boundaries, particularly in addressing the unique challenges posed by AV lane detection tasks.

4. **Establishment of Universally Acceptable Datasets:** The lack of globally standardized datasets tailored to YOLO algorithm training for diverse road environments is a critical challenge. These datasets must encompass variations in road users, lane structures, and traffic signs across different geographical regions. Creating such universal datasets will enable the development of robust, adaptable algorithms that can be integrated seamlessly by AV manufacturers worldwide. Standardized datasets will not only improve YOLO's detection capabilities but also ensure consistency and reliability in global AV applications.

Addressing these challenges will significantly enhance YOLO's efficacy in autonomous vehicle applications, paving the way for safer and more reliable AV systems in real-world environments.

7. Discussion

This section critically examines the findings presented throughout the paper, offering a synthesis that moves beyond descriptive accounts of YOLO-based algorithms to a deeper evaluative perspective. By comparing different YOLO variants, analysing their performance across multiple datasets, and identifying persistent limitations, we contextualize their capabilities within the broader landscape of autonomous vehicle (AV) perception and outline strategic directions for advancing this technology.

7.1. Critical analysis of YOLO's role in AV lane detection and manoeuvres

The YOLO family of algorithms has demonstrated substantial progress in real-time object detection, enabling autonomous vehicles to identify and classify vehicles, pedestrians, traffic signs, and lane markers with increasing accuracy and speed (Hrag-Harouth Jebamikyous, 2022; Ercan Avşar, 2022; Harisankar.R; Mehdi Masmoudi et al., 2019; Jigang Tang and Liu, 2021; Peiyuan Jiang et al., 2021). Compared to traditional, multi-stage detectors like R-CNN variants (Fast/Faster R-CNN and Mask R-CNN), YOLO's single-stage approach reduces latency and computational overhead, making it particularly appealing for AV applications where prompt decision-making is crucial. However, despite these gains, current YOLO algorithms still face difficulty when confronted with challenging real-world conditions. For instance, detecting subtle or degraded lane markings, coping with variable lighting and weather conditions, and handling occlusions or highly cluttered scenes remain non-trivial (Mohanapriya et al.; Cheng Han et al., 2022; Mahaur and Mishra, 2023; Phat Nguyen Huu and Tong Thi Quynh, 2022; Wei Yang et al., 2020; Xiang Zhang et al., 2018).

In addition, while newer YOLO versions (e.g., YOLOv8, YOLOv9, YOLOv10, and YOLOv11) and customized variants (e.g., MAD-YOLO, RDD-YOLO, YOLO-CIR) have pushed the frontiers of speed and accuracy, these improvements often come at the expense of increased model complexity or remain narrowly focused on specific tasks (Jinjie Zhou et al., 2023; Mahaur and Mishra, 2023; Xianchong Xu et al., 2023). Thus, the existing literature collectively illustrates a scenario where incremental advancements in architecture and training protocols yield better performance but do not fully address fundamental challenges that hinder robust, scalable AV deployment.

7.2. Identified gaps and limitations in existing research

A notable gap is the lack of universal, representative datasets covering the full spectrum of road conditions, infrastructure types, and cultural driving practices. Many studies benchmarked their YOLO models on standard datasets such as COCO and KITTI (Peiyuan Jiang et al., 2021; Kim, 2019; Geiger and Lenz, 2013), which, although widely accepted, may not capture the diversity of real-world roadway environments. This limitation constrains model generalizability and may cause YOLO-based AV systems to underperform when introduced to unfamiliar geographic regions or unusual traffic scenarios.

Moreover, current YOLO models struggle with adversarial robustness. Several works have demonstrated the susceptibility of YOLO-based detectors to adversarial perturbations—subtle modifications to the input images that lead to misclassifications or missed detections (Im Choi and Tian; Jia et al., 2022; Wu, 2024; Jiang et al., 2023; Li et al.; Liang et al., 2024). Such vulnerabilities pose serious safety concerns for AVs and emphasize the need for more secure and resilient model architectures and training techniques.

Another key limitation is the balancing act between detection accuracy and computational efficiency. While YOLO excels in speed, pushing the boundaries of accuracy—especially for small objects, distant road signs, or intricate lane configurations—often demands additional layers, complex backbones, or more computational power. Such trade-offs can impede deployment on resource-constrained platforms and limit the algorithm's scalability in large-scale, real-time AV fleets (Mehdi Masmoudi et al., 2019, 2021; Khan et al., 2024; Zillur Rahman and Ullah, 2020).

7.3. Comparisons and key findings

Comparative analyses of YOLO variants show that while incremental architectural improvements (e.g., CSPDarknet backbones in YOLOv4, anchor-free heads in YOLOv8, or gradient enhancements in YOLOv10 and YOLOv11) lead to measurable gains, no single version consistently outperforms all others across every metric and scenario (Mehdi Masmoudi et al., 2019; Abhishek Sarda and Anupama Bhan; Yingfeng Cai et al., 2021; Rui Wang et al., 2021). For example, some YOLO versions excel in ideal lighting conditions yet falter under extreme weather, while

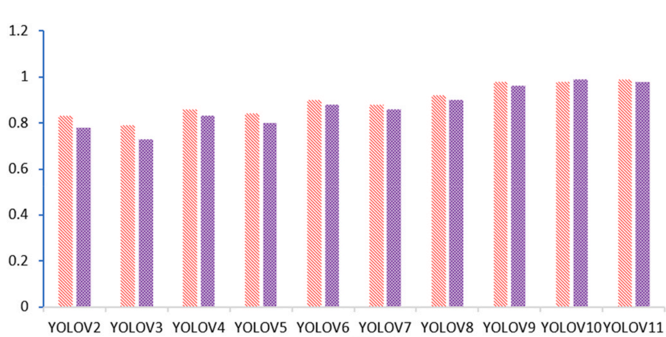


Fig. 6. Comparison of accuracy and precision across different YOLO versions evaluated on the KITTI dataset.

others are optimized for detecting certain object classes at the expense of general-purpose flexibility.

These comparisons highlight the need for adaptive and context-aware detection strategies. It is evident that YOLO-based algorithms must be more than just universally fast—they must be adaptable, robust, and capable of maintaining performance standards across a wide range of real-world challenges.

7.4. Practical and theoretical implications

Practically, the findings suggest that while YOLO can form the backbone of AV perception systems, it remains insufficient as a standalone solution. AV manufacturers and researchers need to consider sensor fusion (e.g., incorporating LiDAR, radar, or thermal imaging) and tailor training protocols to the vehicle's intended environment. This may involve domain adaptation techniques, data augmentation strategies, and extensive real-world testing regimes to ensure consistency and safety in operation (Khayyam et al., 2020; Milani et al., 2020; Al-Saadi et al., 2022; Mahaur and Mishra, 2023).

From a theoretical perspective, YOLO's evolution underscores the importance of balancing model complexity with computational efficiency and generalization capability. The trade-offs observed suggest that further research is needed to develop unified frameworks that seamlessly integrate multi-modal input streams and advanced loss functions while maintaining real-time performance. Additionally, adversarial training and the integration of simulation-based defences will be crucial in fortifying YOLO models against emerging security threats.

7.5. Professional opinions and suggested directions for improvement

Based on the evidence and analyses reviewed, several pathways emerge for improving YOLO-based solutions in AV perception:

1. **Enhanced Training Paradigms:** Adopting meta-learning and neural architecture search can automate the discovery of optimal hyperparameters, loss functions, and model architectures. Semi-supervised learning methods may also help in leveraging large volumes of unlabelled, real-world driving data to improve robustness (Mondschein et al., 2006; Edward Swarlat Dawam, 2020; Yu et al., 2018).
2. **Universal Datasets and Benchmarking Standards:** There is a pressing need for globally representative, standardized datasets that encompass varying lane types, road conditions, weather scenarios, and cultural norms. Such datasets would enable more meaningful cross-comparisons and reliable generalization of YOLO-based models (Mohanapriya et al.; Mahaur and Mishra, 2023; Phat Nguyen Huu and Tong Thi Quynh, 2022; Wei Yang et al., 2020; Xiang Zhang et al., 2018).
3. **Multi-Modal Sensor Fusion:** Integrating camera-based YOLO detection with complementary sensors can improve detection reliability under adverse conditions. Combining LiDAR or radar with YOLO can mitigate vision-only weaknesses, enhancing the model's accuracy in poor visibility or high-occlusion environments (Song et al., 2024; Wang et al., 2024a; Appiah and Mensah, 2024; Silva et al.).
4. **Adversarial Resilience and Safety-Centric Design:** Strengthening YOLO's adversarial resilience through adversarial training, robust simulation platforms, and real-time anomaly detection is essential. Future research could focus on designing specialized YOLO variants or pre-processing modules that detect and neutralize adversarial perturbations.
5. **Architectural Hybridization and Efficiency Optimization:** Incorporating promising features from YOLOv4, YOLOv7, and YOLOv8 (e.g., anchor-free heads, refined attention mechanisms) into hybrid architectures could yield models that strike an improved balance between speed, accuracy, and robustness. Lightweight optimization techniques and hardware acceleration strategies should also be explored to accommodate diverse AV platforms.

8. Conclusion

This comprehensive review was conducted following a systematic and transparent methodology, encompassing a broad literature search across reputable databases, well-defined inclusion and exclusion criteria, and the application of a conceptual framework to categorize, compare, and critically assess the performance of YOLO algorithms in autonomous vehicle (AV) contexts. By integrating both foundational and recent studies, this approach ensured a balanced and in-depth examination of YOLO's evolution, capabilities, and shortcomings. Our analysis revealed that YOLO algorithms excel in providing real-time object detection and lane identification, offering substantial promise for improving AV lane-change manoeuvres and overall navigation. However, persistent gaps hinder the full realization of YOLO's potential. These include difficulty in accurately detecting subtle or irregular lane markings, limited robustness to adverse environmental factors (e.g., variable lighting, occlusions, and adverse weather), and vulnerabilities to adversarial attacks. In addition, the lack of universally representative datasets restricts YOLO's scalability and generalizability across diverse geographical and traffic conditions. Furthermore, issues such as balancing accuracy with computational efficiency remain pressing, especially for resource-constrained AV systems. By synthesizing these findings, this paper highlights YOLO's current limitations and the attendant need for strategic improvements. The contributions of this review extend beyond cataloging existing algorithms and their performance. We have provided a comparative evaluation, identified critical challenges, and proposed avenues for enhancement. Such recommendations include refining YOLO's architectures—potentially by leveraging and hybridizing YOLOv4, YOLOv7, and YOLOv8—to better handle complex and dynamic road environments. Introducing advanced training methodologies, sensor fusion, and hyperparameter tuning, as well as developing global, standardized datasets, can significantly bolster detection accuracy and robustness. Implementing adversarial training and other defensive strategies will further strengthen YOLO's resilience against attacks. In essence, this comprehensive review not only spotlights the strengths and limitations of YOLO algorithms but also provides actionable guidance for future research and practical deployment. By addressing the highlighted gaps and refining YOLO's capabilities, the vision of safe, efficient, and widely scalable autonomous navigation can move closer to reality, making YOLO a cornerstone technology in next-generation AV systems.

CRediT authorship contribution statement

Busuyi Omodaratan: Formal analysis, Conceptualization, Writing – original draft, Software, Data curation. **Ali Jamali:** Conceptualization, Writing – original draft, Investigation, Methodology. **Timothy Wiley:** Data curation, Writing – original draft, Formal analysis, Software. **Ziad Al-Saadi:** Writing – original draft, Methodology, Project administration, Data curation. **Rammohan Mallipeddi:** Software, Conceptualization, Writing – original draft, Data curation. **Ehsan Asadi:** Methodology, Writing – original draft, Investigation, Resources. **Hoshyar Asadi:** Resources, Investigation, Writing – original draft. **Rasoul Sadeghian:** Investigation, Writing – original draft. **Sina Sareh:** Investigation, Writing – original draft, Writing – review & editing. **Hamid Khayyam:** Writing – original draft, Supervision, Writing – review & editing, Visualization, Data curation.

Declaration of competing interest

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

Data availability

No data was used for the research described in the article.

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