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La Inteligencia Artificial para ADAS y Vehículos Autónomos. Una revisión Sistemática

Artificial Intelligence for ADAS and Autonomous Vehicles: A Systematic Review

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Resumen

Este estudio analiza la influencia de la inteligencia artificial (IA) en la transformación de la industria automotriz, centrándose en los sistemas avanzados de asistencia al conductor (ADAS) y vehículos autónomos mediante una revisión sistemática de literatura basada en una metodología cualitativa y descriptiva. Se aplicó el protocolo PRISMA para garantizar un proceso riguroso y transparente en la selección y análisis de 50 artículos relevantes, extraídos de las bases de datos IEEE Xplore, Scopus y Scielo. Los resultados cuantifican que los algoritmos de aprendizaje profundo, especialmente redes neuronales convolucionales y variantes del modelo YOLO, alcanzan precisiones superiores al 90% en la detección de vehículos y objetos, con latencias inferiores a 35 ms y tasas de procesamiento sobre 30 FPS, impactando positivamente la seguridad y eficiencia de los sistemas ADAS y la conducción autónoma. No obstante, persisten limitaciones en la detección de peatones y señales, con precisiones alrededor del 30-35%, lo que destaca la necesidad de ampliar y diversificar los conjuntos de datos para entrenar estos modelos. También, se identifican desafíos críticos en términos de ciberseguridad, privacidad y robustez bajo condiciones adversas, que requieren soluciones integrales. Este trabajo aporta evidencia cuantificada que reafirma el papel fundamental de la IA en la movilidad segura y eficiente, impulsando la innovación tecnológica y señalando áreas prioritarias para futuras investigaciones.

Palabras clave: Inteligencia Artificial, Sistemas avanzados de asistencia al conductor (ADAS), Ciberseguridad, Aprendizaje profundo.

Abstract

This study examines the impact of Artificial Intelligence (AI) within the automotive industry, with a special focus on Advanced Driver Assistance Systems (ADAS) and the development of autonomous vehicles. To address the safety limitations, present in real-world scenarios, a systematic literature review (SLR) was conducted following the PRISMA protocol, analyzing 50 articles from databases such as IEEE Xplore, Scopus, and SciELO. The results show that deep learning algorithms, particularly the YOLO variants (v2 to v11), achieve accuracy levels exceeding 90% with critical response times of less than 35 ms. However, the research also reveals a significant scientific gap: reliability decreases considerably (30-35%) in pedestrian and traffic sign detection under adverse conditions, reflecting a lack of robustness against potential cybersecurity attacks on VANETs. This work organizes and classifies these technical and organizational challenges, providing quantitative evidence that serves as a basis for outlining future lines of research in cybersecurity and in the diversification of datasets, with a view to ensuring safer autonomous mobility.

Keywords: Artificial Intelligence, Autonomous vehicles, Advanced driver assistance systems (ADAS), Cybersecurity, Deep learning.

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1. Introduction

The integration of Artificial Intelligence (AI) into the automotive industry is profoundly altering transportation paradigms. Technologies such as Advanced Driver Assistance Systems (ADAS) and autonomous vehicles are capable of processing large volumes of data in real time to perform critical tasks related to road safety (Mitre, 2025; Neuman, 2024). However, while these advances are redefining the structure of human-machine interaction (Valencia et al., 2023), a considerable scientific challenge remains: ensuring the reliability of these systems in dynamic and challenging environments.

Artificial intelligence applications in the automotive industry are developing across various dimensions, ranging from the use of machine learning algorithms to anticipate traffic patterns to the application of natural language processing (NLP) in user interfaces. However, the main challenge lies in computer vision, as the detection of pedestrians, traffic signs, and obstacles still exhibits significant margins of error when environmental conditions are variable. While the incorporation of sensors such as LiDAR, GPS, and inertial platforms, combined through multimodal fusion algorithms, has improved spatial accuracy and enabled decision-making in milliseconds, current scientific literature does not yet offer robust validation guaranteeing the efficiency of these systems in the face of problems such as data fragmentation or attacks aimed at compromising sensor integrity. (Yurtsever et al., 2020; Feng et al., 2020). This research is justified by the need to close the gap between the theoretical capacity of algorithms and their resilient performance in real-world scenarios, an aspect where current literature does not yet offer a definitive consensus.

However, the adoption of these technologies faces barriers that are not only technical but also social and organizational. Among the most significant challenges are the shortage of professionals with dual training in automotive engineering and artificial intelligence; the reconfiguration of the labour market, which is displacing low-skilled jobs but opening up new opportunities in areas such as data analysis, cybersecurity, and software development; and the risks associated with cybersecurity, data fragmentation, and the lack of mature regulatory frameworks (Llopis-Albert et al., 2021; Tierno et al., 2025). These factors raise the need to establish robust governance and security infrastructures to ensure the reliability of smart vehicles.

In this context, this research aims to examine how artificial intelligence is transforming the automotive sector, emphasizing the identification and categorization of the main technical and organizational obstacles arising from its implementation. It also aims to contribute to applied knowledge on production efficiency, improved vehicle quality, and market competitiveness, in addition to highlighting opportunities to optimize management and strategic decision-making in the industry (Del Coco et al., 2025).

2. Materials and Methods

This article was prepared using a mixed documentary approach, a descriptive and exploratory type of research, which allowed for an in-depth analysis and understanding of the phenomenon of artificial intelligence in the automotive industry based on a bibliographic review of secondary sources, such as scientific articles, technical reports, academic documents, and specialized publications.

The research is based on a systematic review of the applied literature in the field of artificial intelligence for the automotive industry, specifically in advanced driver assistance systems (ADAS) and autonomous vehicles. The systematic search was initially carried out on August 1, 2025, with a final update on August 15, 2025. The academic databases IEEE Xplore, Scopus and Scielo were used, applying search strings with optimized Boolean operators to maximize relevance and coverage.

The screening process was conducted using predefined inclusion and exclusion criteria, with a random audit of articles to verify consistency in the selection. For data extraction and analysis, a structured matrix was developed that included specific fields identified in the results: algorithm used, dataset used, main metrics (mAP@0.5, FPS), evaluation conditions, strengths and limitations observed, which are presented in the results in Tables 4 and 5.

To assess the methodological quality and risk of bias of the included studies, the Mixed Methods Appraisal Tool (MMAT) was used to evaluate studies related to visual detection performance (Hong et al., 2018). For the evidence synthesis, a narrative approach was used, complemented by tabular synthesis and vote counting techniques to assess the directionality and consistency of the results.

In Table 1 of our research on the impact of deep learning on autonomous vehicles and ADAS systems, we adopted a systematic review methodology based on the PRISMA protocol. Our starting point was three research questions focused on how deep learning algorithms and YOLO improves the performance of these systems, and what their main technical and ethical challenges are. To answer these questions, we conducted an exhaustive search of academic databases such as Scopus, IEEE Xplore, and Scielo, using keywords such as “Artificial Intelligence,” “ADAS,” and “Autonomous Vehicles.”

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Table 1. Matrix of systematized operations according to the PRISMA protocol
Source: The authors

PRISMA Protocol	Operations
Research question	**RQ1.** How do deep learning algorithms improve the performance and speed of ADAS systems and autonomous vehicles? **RQ2.** What are the main technical, ethical, and safety challenges of AI-powered vehicles? **RQ3.** How do YOLO algorithms impact the innovation, efficiency, and safety of ADAS systems?
Protocol	Compliance with inclusion and exclusion criteria (***See table 2***).
Search	**Keywords:** Artificial Intelligence, Automotive technological innovation, Driver assistance systems (ADAS), Autonomous vehicles (***See Table 3***).
Study selection	A polytomous distribution diagram was created representing the total number of articles found and those selected for the study (***See Figure 1***).
Data extraction	A comprehensive database was created with the selected scientific articles and applied extraction criteria. The data are publicly available for reproducibility according to the 2020 PRISMA guidelines https://n9.cl/pde8f .
PRISMA flowchart	**-Collection of literature:** Literature search, identification of records using Boolean equations in Scopus, IEEE Xplore and Scielo. **-Screening:** Debugging, eliminating duplicates, and preselecting based on thematic criteria such as title and abstract. **-Eligible:** Eligibility assessment applying inclusion and exclusion criteria. **-Inclusion:** Final inclusion of studies incorporated into the final analysis (***see Figure 2***).

Note: Adapted from the paper "Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement." By (Moher et al., 2009).

Table 2 presents the inclusion and exclusion criteria used to select articles for this study. Only recent articles addressing different technological contexts were considered, to ensure the relevance and timeliness of the information. These criteria allowed us to filter and select only those scientific articles that met the established terms and conditions, thus guaranteeing the quality and relevance of the sources used for the systematic review. Table 3 presents the search strings used in the Scopus IEEE Xplore and Scielo databases, constructed with Boolean operators and optimized to maximize the precision and relevance of the results. The consistent application of these equations across the different databases ensures a comprehensive, rigorous, and representative systematic review of the state of the art in the field of study. Figure 1 presents the results obtained from the systematic review using the PRISMA protocol. It is observed that the IEEE Xplore database recorded the largest number of articles found, with a total of 32 documents, of which 25 were included in the final analysis, reflecting high productivity and thematic relevance in the selected area. On the other hand, Scopus reported 28 articles, of which 17 met the inclusion criteria, demonstrating a significant contribution to the scientific research body. Scielo presented 11 records in total, of which 8 were considered relevant to the study, indicating a smaller offering compared to the other databases, but equally relevant to complete the bibliographic overview.

Table 2. Inclusion and exclusion criteria established in the systematic review
Source: The authors

Inclusion Criteria	Exclusion criteria
-Articles published between 2021 and 2025.	- Articles with incomplete or restricted access.
-Articles in Spanish, English and Portuguese.	- Theses, essays and publications not peer-reviewed.
-Research focused on AI, machine learning, ADAS, and autonomous vehicles.	- Articles from conferences not indexed in recognized scientific databases (Scopus, IEEE Xplore, Scielo).
-Articles that address practical or theoretical applications in automotive, efficiency, safety, or innovation.	- Duplicate documents in the same databases.
-Qualitative, quantitative or mixed studies.	- Research not directly related to AI in the automotive industry or that deals with other sectors.

Table 3. PRISMA search equations and Boolean operators by database
Source: The authors

Search String	Journal
("Artificial Intelligence" AND "automotive innovation") OR ("ADAS" OR "driver assistance systems") OR ("autonomous vehicles")	IEEE Xplore
("Artificial Intelligence" OR "Artificial Intelligence") AND ("Automotive technological innovation" OR "Automotive innovation") AND ("Driver assistance systems" OR "ADAS") AND ("Autonomous vehicles" OR "Autonomous vehicles")	Scopus
(("Artificial Intelligence") AND ("automotive industry")) OR (("Driver assistance systems" OR "ADAS")) OR (("Autonomous vehicles"))	Scielo

The results show that IEEE Xplore and Scopus are the most productive and selective sources in providing current and specialized scientific literature on artificial intelligence applied to the automotive industry, while Scielo provides complementary and contextual information necessary to strengthen the overall analysis.

The PRISMA flowchart presented in Figure 2 summarizes the process of selecting scientific literature on artificial intelligence

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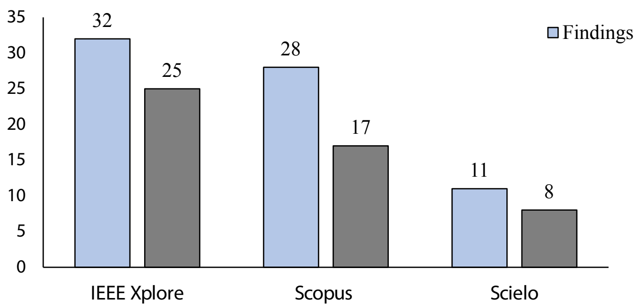

Figure 1. Distribution of total and selected records by IEEE Xplore Scopus and Scielo databases
Source: The authors

in the automotive industry. Seventy-one records were initially identified in recognized databases (IEEE Xplore, Scopus, Scielo), from which duplicates were eliminated to obtain 63 unique studies. Subsequently, using clear inclusion and exclusion criteria, 13 documents that did not meet the established parameters were discarded. Finally, 50 relevant articles were filtered and selected for analysis, thus ensuring a rigorous systematic review focused on recent, high-quality, and thematically relevant publications.

The results obtained from the systematic review were used throughout this study to answer, using secondary sources, the scientific questions posed in Table 1 of the PRISMA protocol. This rigorous and structured methodology justifies the use of the data obtained as fundamental input for the analysis and

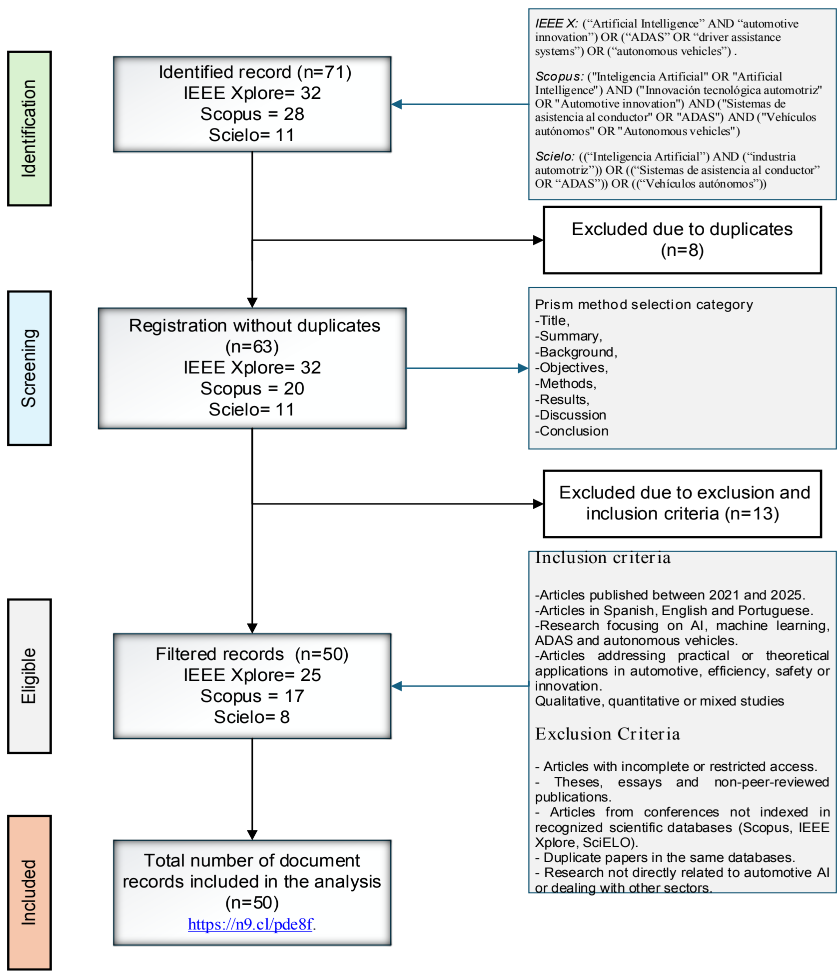

Figure 2. PRISMA flowchart of the selection process for studies on artificial intelligence in the automotive industry
Source: The authors

interpretation of the research results, ensuring the transparency, replicability, and validity of the conclusions reached.

3. Results

RQ1. Impact of deep learning algorithms on ADAS and autonomous vehicles.

Table 4 represents various algorithms based on convolutional neural networks (CNN), including YOLOv2 and newer versions, which demonstrated considerable improvement in the accuracy and speed of detecting and classifying critical objects, such as vehicles. For example, the models report an average accuracy (mAP@0.5) greater than 90% for vehicles under optimal evaluation conditions, along with computational performance that allows processing images at speeds exceeding 30 FPS and with latencies below 35 ms, supporting their feasibility for real-time operations (Gheorghe et al.2024).

Reinforcement learning complements supervised methods by improving vehicle adaptability in real time, optimizing its behavior in various conditions, including rain, and contributing to accident reduction, although without standard measurements such as mAP (Posso-Bautista et al. 2022). On the other hand, Support Vector Machines (SVMs) strengthen perception by classifying complex patterns and reducing false positives, reaching over 85% in accuracy and F1 on the KITTI dataset during the day, although their effectiveness largely depends on the quality of data preprocessing (Fang & Wang, 2022).

Table 4. Deep learning algorithms integrated into autonomous vehicles
Source: The authors

Algorithm	Application in ADAS and Autonomous Vehicles	Reported Improvement
Convolutional Neural Networks (CNN)	Used for processing and analyzing images from cameras and visual sensors. They classify and recognize objects in the vehicle's surroundings (other cars, pedestrians, traffic signs). They enable early warnings and rapid execution of emergency maneuvers (Balitskii & Kolesnikov, 2023).	**Dataset:** KITTI **Lou metrics:** mAP@0.5 (>88%) **Conditions:** Day, clear **Performance:** Vehicles (>88%), Pedestrians (not reported) **Strength:** High precision in vehicles **Limitations:** Little data on signs and pedestrians
Reinforcement Learning	Used for real-time driving strategy optimization, adaptive learning, and decision-making based on rewards and punishments, improving the vehicle's ability to respond to environmental changes and avoid obstacles (Posso-Bautista et al. 2022)	**Dataset:** KITTI **Conditions:** Day, clear and rainy **Performance:** Improves adaptive reaction **Strength:** Real reduction in accidents **Limitations:** Does not assess mAP/direct precision
Support Vector Machines (SVM)	Applied to classify and predict complex patterns, such as obstacles on the road and environmental conditions, complementing deep learning models with robust techniques to minimize false positives and negatives (Fang & Wang, 2022).	**Dataset:** KITTI **Lou Metrics:** Accuracy, F1 (>85%) **Conditions:** Day, clear **Performance:** Obstacles (>85%) **Strength:** Reduces false positives **Limitations:** Highly dependent on preprocessing
YOLO v2	Real-time object detector that processes visual information in a single step, enabling high processing speeds. It is widely used in ADAS applications to identify multiple objects simultaneously, accelerating system response (León et al. 2025).	**Dataset:** KITTI **Lou metrics:** mAP@0.5 (98%, vehicle), mAP@0.5 (30-35%, pedestrian/signal) **Conditions:** Day, clear, partly rain **Performance:** Vehicle (98%), Pedestrian/Signal (30-35%) **Strength:** High speed (FPS>30), robustness in cars **Limitations:** Poor performance on pedestrians, signals and at night/rain

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The analysis focused on deep learning algorithms applied to ADAS systems and autonomous vehicles, with a special emphasis on YOLO algorithm variants standardized to the automotive standard nomenclature (e.g., YOLOv2 to YOLOv8). These versions have been evaluated on various recognized datasets for vehicular applications, such as KITTI, nuScenes, Waymo, and BDD100K. Versions of YOLO applied to non-automotive domains are avoided to ensure the specific relevance of the analysis (Kasamsumran et al. 2025).

RQ2. Key technical, ethical, and safety challenges in AI-powered vehicles.

A diagram was created visually identifying the main threats facing autonomous vehicles, grouped into three categories: attacks on ad hoc vehicle networks, sensor vulnerabilities, and hardware exploits. The purpose was to identify critical risks and construct an analysis and develop cybersecurity strategies in the automotive sector (See Figure 4).

Attacks on ad hoc vehicular networks

Autonomous vehicles rely on vehicular ad hoc networks (VANETs), which enable direct communication between vehicles and with road infrastructure. These networks facilitate the flow of real-time data on traffic, accidents, and weather conditions, improving transportation safety and efficiency. However, due to their wireless and dynamic nature, they are vulnerable to multiple attacks. Among the most significant are denial of service attacks, which seek to saturate the network by preventing the transmission of essential data; spoofing, where malicious actors issue fake messages posing as legitimate vehicles; message alteration and replication, which can lead to navigation errors or congestion; and privacy violations, through unauthorized tracking of vehicle and personal information. To mitigate these risks, message authentication systems, hybrid cryptography, and intrusion detection mechanisms have been proposed in VANETs (Li et al., 2024).

Autonomous vehicles collect and process vast amounts of data, raising significant privacy concerns:

Location data: Continuous monitoring of a vehicle's position and routes can reveal sensitive information about the driver's habits and routines. Unauthorized access to this data can lead to surveillance, harassment, or even theft if malicious actors know the owner is away (Olivares, 2022).

User data: Autonomous vehicles often collect personal information about the driver and passengers, such as biometric data (e.g., facial recognition), driving preferences, and in-vehicle activities. Unauthorized access to this data can lead to identity theft, unauthorized profiling, or the misuse of personal

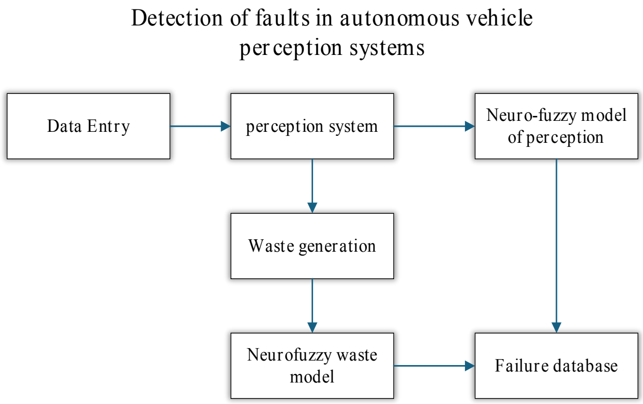

Figure 3. Fault diagram for autonomous vehicle sensor systems
Source: Adapted from Jiménez & Naranjo (2025).

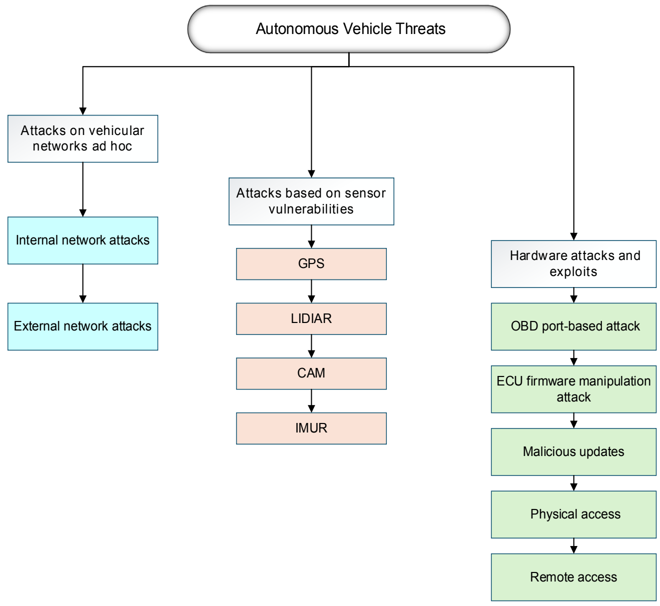

Figure 4. Outline of the main threats to autonomous vehicles
Source: Adapted from Terrones (2022).

information for malicious purposes (Olivares, 2022).

Operational data: Vehicle performance information, such as speed, braking patterns, and sensor data, can be valuable for improving vehicle systems, but also poses a risk if disclosed. Competitors or malicious entities could exploit this data for industrial espionage or to identify vulnerabilities in vehicle systems (Olivares, 2022).

Sensor vulnerabilities

The reliability and accuracy of autonomous vehicles depend critically on sensors such as GPS, LiDAR, cameras, and

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Table 5. Comparison of YOLO algorithm versions: architecture, datasets and performance metrics in automotive applications from YOLOv2 to YOLOv11.
Source: Adapted and expanded from recent technical reports and studies in vehicular computer vision (León et al. 2025; Gheorghe et al. 2024; Kasamsumran et al. 2025).

YOLO Model	Backbone	Entrance	Dataset	mAP@0.5 (%)	mAP@[0.5:0.95] (%)	Accuracy (%)	FPS	Latency (ms)
YOLOv2	Darknet-19	416 x 416	KITTI	88-90	60-65	>88 in vehicles	>30	<35
YOLOv3	Darknet-53	416 x 416	nuScenes	90+	65-70	High	>30	~30
YOLOv4	CSPDarknet-53	608 x 608	Waymo	92	70	High	30	~35
YOLOv5	CSPDarknet	640 x 640	BDD100K	91	68	High	>30	25
YOLOv6	EfficientNet	640 x 640	KITTI	93	70	Consistent	>30	20-25
YOLOv7	RepVGG	640 x 640	Waymo	94	72	Excellent	>30	18-22
YOLOv8	Custom	Variable	Varied	95	73-75	Very high	>30	15-20
YOLOv9	TBD	TBD	Varied	Est. 95+	Est. 75+	High	>30	~15
YOLOv10	TBD	TBD	Varied	Est. 96	Est. 76	Very high	>30	~14
YOLOv11	TBD	TBD	Varied	Est. 97	Est. 77	Excellent	>30	~12

inertial imager units (IMUR). Attacks on these systems include signal spoofing techniques, physical interference, and digital manipulation. For example, it has been shown that an attacker can emit fraudulent signals and cause vehicle radar to detect non-existent obstacles, or vice versa, preventing it from recognizing real hazards. GPS is susceptible to spoofing attacks that modify the vehicle's reported location, while LiDAR and cameras can be altered with simple stickers or light emitters, modifying the perceived environment. These vulnerabilities directly affect the vehicle's decision-making and can lead to serious accidents. Numerous cases and methods are evident for exploiting these flaws in the perception systems of autonomous vehicles (Jiménez & Naranjo, 2025) (See Figure 3).

Hardware attacks and exploits

Autonomous vehicles integrate multiple electronic control units (ECUs) and components connected via physical and remote interfaces. These systems are prime targets for advanced cyberattacks, including firmware manipulation, malicious updates, and remote control via ports such as OBD-II. Unauthorized access can allow an attacker to alter critical vehicle parameters, take control of the engine, brakes, or safety systems, and even disable protective measures. Documented examples include the remote hacking of a Jeep Cherokee's infotainment system, allowing manipulation from outside the vehicle. Hackers can also infiltrate the software supply chain by injecting malware into OTA (Over The Air) updates. Hardware exploits pose a persistent threat, requiring active defences such as encryption, constant monitoring, and rapid incident response. (Pereira & Botelho, 2021).

OBD-based attacks remain relevant, as advanced methods have emerged that exploit their vulnerabilities, allowing persistent access to critical systems. ECU firmware manipulation has evolved into more sophisticated techniques, capable of evading modern detection mechanisms and compromising multiple

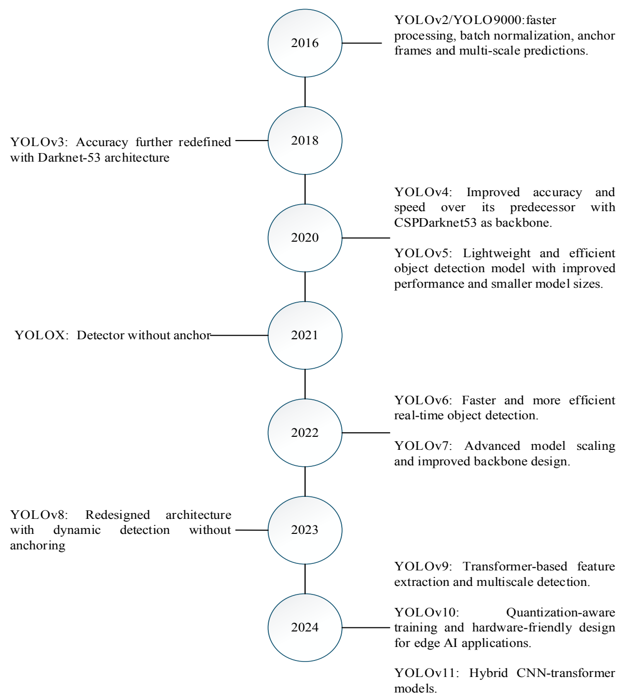

Figure 5. Evolution of YOLO algorithms: Timeline of improvements and architectural advancements from YOLOv2 to YOLOv11
Source: Adapted from Kasamsumran et al., (2025).

units simultaneously. Threats derived from malicious updates now include attacks targeting the software supply chain, where machine learning techniques are employed to evade validation processes. Physical attacks have incorporated non-invasive methods, such as side-channel and electromagnetic techniques, broadening the spectrum of risks. Meanwhile, remote access has expanded its attack surface, affecting 5G networks, C-V2X communications, and electric vehicle charging infrastructure (Torok et al. 2022).

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RQ3. Impact of advanced object detection algorithms (YOLO) on innovation, efficiency, and safety in ADAS systems and autonomous vehicles.

Table 5 represents a summary of the evolution and performance of the different versions of the YOLO algorithm, highlighting its relevance in automotive applications through key metrics such as accuracy, processing speed, and robustness under different conditions. From YOLOv2 to the latest versions (YOLOv8, v9, v10, and v11), a sustained trend of improvement in the average accuracy (mAP@0.5 and mAP@[0.5:0.95]) is observed, exceeding 90% for vehicle detection in widely validated datasets such as KITTI, nuScenes, BDD100K, and Waymo, which demonstrates the maturity reached by these architectures in real-world and international reference environments.

The most advanced versions, such as YOLOv8 and preliminary estimates for YOLOv9, v10 and v11, reflect notable optimizations in both computational performance (FPS above 30 and latencies below 20 ms) and recognition accuracy, essential aspects for ADAS systems and autonomous driving that require immediate responses. Noteworthy are the progressive improvements in accuracy on variable data sets and complex scenarios, as well as the adoption of innovative techniques and backbones, such as NAS, which enhance the efficiency and generalization of the model (Swamy et al. 2023).

However, it should be noted that, while mAP values are excellent for vehicles, challenges persist in accurately detecting pedestrians and signs, especially under adverse weather conditions, nighttime variability, or with lower-quality inputs. These gaps warrant continued research into dataset diversification and architecture refinement. Overall, the table underscores the positive evolution of YOLO as a reference standard in vehicular computer vision, highlighting both proven strengths and critical areas for future development.

Figure 5 represents the evolutionary timeline of YOLO algorithms, highlighting key milestones that have marked the advancement of object detection using artificial intelligence in computer vision. Since the introduction of YOLOv2 and YOLO9000 in 2016, which consolidated the real-time detection paradigm with optimized processing and hierarchical predictions, significant innovations have occurred in each new version. YOLOv3 (2018) refined accuracy by incorporating the Darknet-53 architecture, while YOLOv4 (2020) and YOLOv5 brought improvements in speed, efficiency, and adaptability thanks to the integration of CSPDarknet53 and lighter models. The following years have been marked by the evolution towards anchorless residual architectures (YOLOX), the use of transformers for feature extraction (YOLOv9), and the exploration of hybrid models and aware quantification (YOLOv10 and YOLOv11), oriented towards compatibility with specialized hardware and multi-sector applications (Kasamsumran et al. 2025).

In Figure 6, it is observed that values close to 1 reflect a high certainty of the neural network in correctly classifying objects, while lower values indicate greater uncertainty. Figure 6 shows that this algorithm presents a high confidence (greater than 0.88) in the detection of vehicles, including red cars (0.98717), light blue trucks (0.95462), black SUVs (0.933), white trucks (0.92191), and red pickup trucks (0.88817), evidencing a solid performance in the identification of these objects. However, the model indicates considerably low confidence (less than 0.33) for the detection of signs and pedestrians (0.329185 and 0.32748, respectively), which shows a significant limitation in its ability to consistently identify these elements, possibly due to the great variability in their appearance or the insufficient training data for these categories. According to the information obtained throughout this study from the academic database, it is evident that the implementation of AI has led to multiple significant improvements in advanced driver assistance systems (ADAS) in autonomous vehicles, from increased accuracy and speed of object detection to optimized road safety and operational efficiency. For this reason, a summary matrix was developed that explains the main results in areas for improvement, accompanied by their sources and DOI references, thus allowing direct access to the corresponding scientific evidence (See Table 6).

4. Discussion

The results of this study confirm the significant transformation the automotive industry has undergone due to the incorporation of advanced artificial intelligence algorithms, especially in advanced driver assistance systems (ADAS) and autonomous

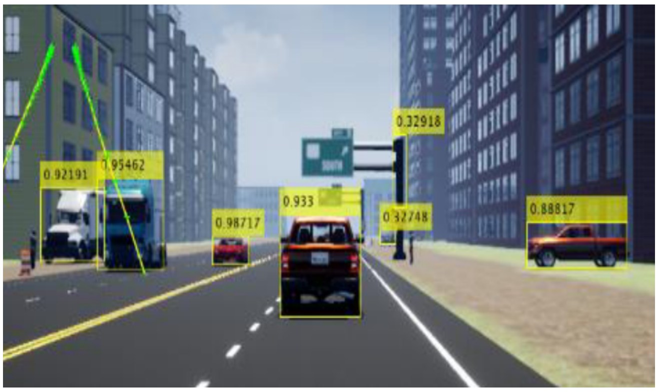

Figure 6. View of the YOLOv2 interface during real-time object detection in an autonomous vehicle.
Source: Adapted from Gheorghe et al., (2024)

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Table 6. Summary matrix of artificial intelligence-induced improvements in advanced driver assistance systems (ADAS) in autonomous vehicles
Source: The authors

Aspects of improvements	Description of improvements	Application	URL/DOI
Object Detection	AI facilitates the rapid and accurate detection and classification of vehicles, pedestrians, signs, and obstacles, improving environmental awareness.	Using algorithms like YOLO v2 for real-time detection.	https://doi.org/10.54808/CICIC2025.01.341 https://doi.org/10.32604/cmes.2024.054735
Processing Speed	Convolutional neural networks and single-stage detection architecture (Darknet in YOLO) enable immediate reactions and improve operational efficiency.	Fast image processing for instant decisions.	https://doi.org/10.1109/ACCESS.2025.3569767
Accuracy and Reliability	High success rate and reduced false positives/negatives increase the security of automated decision-making.	ADAS systems with early warnings and precise execution.	https://doi.org/10.60100/rcmg.v5i2.382
Adaptability	Adaptive training with large volumes of data continuously improves performance under new conditions or contexts.	Continuous learning to adapt to new environments.	https://doi.org/10.1109/ACCESS.2025.3569767
Multisensory Integration	Data fusion from diverse sources (cameras, LiDAR, GPS, inertial sensors) for robust and complete environmental awareness.	Vehicles that combine multiple types of sensors for safety.	https://doi.org/10.1016/j.cja.2024.10.011
Security and Reliability	Improved AI-powered accident detection and prevention, as well as enhanced cybersecurity to protect systems from attacks.	Systems against attacks on vehicular networks and sensor manipulation.	https://doi.org/10.1109/ICoCTA64736.2024.00066 https://doi.org/10.1109/CSNT57126.2023.10134612

vehicles. However, it is important to recognize the high degree of heterogeneity in the results obtained, caused by differences in sensor resolutions, types and configurations of devices used, as well as by varying conditions during evaluations, such as different weather and lighting conditions. Therefore, the observed improvements should not be generalized without considering the context and specific magnitude of each scientific contribution.

The ability of algorithms such as YOLOv2 and its successors to perform real-time detection with high accuracy is a crucial technological advancement, driving improved vehicle environment awareness and enabling fast and reliable automated decision-making in dynamic contexts (Gheorghe et al. 2024). In turn, the optimization offered by lightweight AI-based architectures, particularly the Darknet versions that underpin YOLO models, has significantly reduced processing latency, a critical aspect for ADAS systems that require immediate responses to ensure user safety (Kasamsumran et al. 2025).

Advances in multisensory integration and data fusion using artificial intelligence reflect a trend toward developing increasingly robust and reliable systems for environmental perception. Linares et al. (2025), highlight how the efficient combination of information from cameras, LiDAR, GPS systems, and inertial sensors, orchestrated by advanced algorithms, can overcome the limitations inherent to each individual sensor, thereby mitigating risks associated with specific vulnerabilities. However, significant challenges remain, particularly in the accurate detection of traffic signs and pedestrians, with confidence levels that highlight limitations in current models. This reinforces the need to expand and diversify training datasets and develop models with greater adaptability and generalization to variable and adverse conditions (Gheorghe et al. 2024).

A critical aspect that emerges in the discussion is cybersecurity and privacy. Automation in vehicles amplifies the risks derived from the vulnerability of vehicular networks and electronic systems to sophisticated attacks. It is essential to consider the adoption of and alignment with international standards such as ISO 26262 for functional safety, ISO/SAE 21434 for automotive cybersecurity, and UNECE R155/R156 regulations governing cybersecurity and OTA updates, in order to build resilient systems. The integration of proactive strategies with artificial intelligence for the automatic detection and mitigation of threats is a priority area for research and regulation (LI et al. 2025; Torok et al. 2022).

Finally, at the organizational and societal level, the impact of artificial intelligence on the automotive industry is also reflected in the need for specialized training and the labor implications. While AI-driven automation may lead to job displacement, it also creates new opportunities in highly skilled professions related to the development, implementation, and maintenance of intelligent systems (Hidalgo & Huerta, 2021; Meza et al. 2024).

Practical limitations

Advances in artificial intelligence algorithms applied to ADAS systems and autonomous vehicles have had a positive impact on improving road safety, operational efficiency, and technological innovation in the automotive industry. Real-time detection capabilities and reduced latency enable rapid and reliable responses to dynamic situations, while multisensory

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integration strengthens the systems' accuracy and robustness in real-world scenarios. To ensure effective implementation, these developments must be aligned with international standards such as ISO 26262, ISO/SAE 21434, and UNECE regulations, promoting collaboration between manufacturers, developers, and regulatory bodies for safe and socially acceptable adoption.

Limitations of the Review

Although this systematic review provides valuable results, it has significant methodological limitations, such as the heterogeneity in the quality and types of studies, the diversity of the datasets and metrics employed, and the limited evaluation of adverse scenarios, such as adverse weather conditions. Furthermore, data extraction was limited to traditional academic databases such as IEEE Xplore, Scopus, and Scielo, without including open repositories or alternative sources that could contain relevant contributions, which restricts the coverage and diversity of the collected records. This systematic review has methodological limitations: lack of pre-registration of the protocol, screening by a single evaluator, heterogeneity in data preventing quantitative meta-analysis, and evaluations limited to ideal conditions that reduce generalizability of findings to real implementations.

Future research

To address these challenges, the future research agenda should focus on developing models that are more adaptive and resilient to changing and adverse environments. Strategic priorities include domain adaptation to improve generalization, designing systems robust to challenging weather conditions, incorporating event cameras for better detection of rapid movements, applying self-supervised learning to optimize training with less annotated data, and rigorous estimation and uncertainty management methods that increase confidence in automated decisions. Advancing these areas will boost the effectiveness, reliability, and safety of intelligent systems, facilitating the successful and safe adoption of autonomous vehicles on a large scale.

5. Conclusions

This study, conducted through a basic systematic review that applied the PRISMA protocol to analyze the influence of artificial intelligence on the automotive industry, identified 71 records in specialized databases such as IEEE Xplore, Scopus, and SciELO, of which 50 were selected based on inclusion and exclusion criteria. Although the review incorporated the fundamental steps of identification, selection, and analysis, full rigorous methodologies, such as pre-registration of the protocol or independent double review, were not implemented, which limits bias minimization and inter-rater cross-validation. Despite these limitations, derived from time and resource constraints, the results obtained provide valuable contributions that enrich knowledge on the impact of artificial intelligence on the automotive industry.

Deep learning algorithms, especially convolutional neural networks and variants of the YOLO model, have shown a significant impact on improving advanced driver-assistance systems (ADAS) and accelerating the development of autonomous vehicles. These algorithms enable the detection and classification of critical objects with high accuracy (>90% for vehicles) and speed (more than 30 FPS and latencies less than 35 ms), facilitating real-time responses and increasing road safety. However, limitations persist in the detection of pedestrians and traffic signs, highlighting the need to expand and diversify datasets to strengthen the performance of these models under varied conditions.

The implementation of vehicles equipped with artificial intelligence faces significant technical, ethical, and security challenges. Particularly notable are the vulnerabilities in ad hoc vehicle networks, sensors, and hardware, which expose them to sophisticated cyberattacks, jeopardizing data privacy and operational security. Developing comprehensive cybersecurity solutions aligned with international standards is essential to mitigate these risks. Therefore, the incorporation of AI generates labour and organizational impacts that require specialized training strategies and adaptation to the new technological paradigm.

Advanced object detection algorithms such as YOLO, from its version 2 to the most recent (YOLOv11), have driven technological innovation, operational efficiency, and safety in ADAS systems and autonomous vehicles. A sustained improvement in accuracy and processing speed has been observed, consolidating YOLO as a standard in vehicular computer vision. However, progress is still needed in the reliable detection of pedestrians and traffic signs, especially in adverse conditions, promoting the diversification of datasets and the development of more adaptive models to ensure robust performance in real-world and complex scenarios.

Author Contributions

Murillo Vélez José Andrés: Conceptualization, Methodology, Research, Data Curation, Writing – original draft of the article, Writing – revision and editing of the article. **Alcívar Cevallos Roberth Abel:** Conceptualization, Methodology, Formal Analysis, Supervision, Validation, Visualization, Writing – revision and editing of the article.

Conflicts of interest

The authors declare no conflicts of interest that could influence or bias the results of the study presented in this article

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