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Review

Recent Progress on Automotive Lane Departure Warning Systems: A Systematic Review of the Complete Pipeline

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Abstract

Lane departure warning systems (LDWS) alert the driver, or intervene through steering, before an unintended lane departure occurs. Earlier reviews that covered lane tracking and warning predate deep learning-based lane detection, while recent reviews treat detection in isolation. Following PRISMA 2020, this systematic review covers the complete pipeline: searches of OpenAlex and IEEE Xplore, supplemented by Consensus, yielded 695 included studies published since 2018. It traces lane detection and its benchmarks across three methodological eras (classical, two-dimensional deep learning, and three-dimensional and transformer-based methods) and extends to tracking, warning decision logic, including current regulatory tests, and steering intervention. Two-dimensional detection has converged on established benchmarks with high reported accuracy, whereas the later stages remain less standardised in evaluation, and deployed systems behave differently from designs validated in simulation. The benchmarks come mainly from structured roads in North America, Europe, and East Asia. Evidence from Malaysia, where motorcycles account for 46 percent of registered vehicles and 63 percent of road deaths, suggests that mixed traffic, worn markings, and rain remain underrepresented, and that methods trained on these benchmarks lose accuracy on local roads. These gaps are priorities for research and regulatory tests.

Keywords: lane departure warning; lane detection; advanced driver assistance systems; deep learning; steering intervention

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1. Introduction

According to the World Health Organization (WHO), road traffic crashes kill approximately 1.19 million people each year and injure up to 50 million more, making road traffic injury the leading cause of death for people aged 5 to 29 [1]. Single-vehicle road departure crashes account for a substantial share of this toll, and unintended lane departure caused by driver inattention, drowsiness, or distraction remains one of the most common precursors to these crashes [2,3]. Lane departure warning systems (LDWS) and the closely related lane keeping assist (LKA) systems address this problem (Figure 1). Both estimate the position of the host vehicle relative to the lane boundaries in real time and either alert the driver or intervene through the steering system before an unintended departure occurs. Field studies of deployed systems report meaningful reductions in real-world lane departure crashes attributable to LDWS and LKA [4,5]. This evidence has led regulators and manufacturers to treat these systems as a transport safety priority, and it increasingly shapes decisions about mandating their deployment.

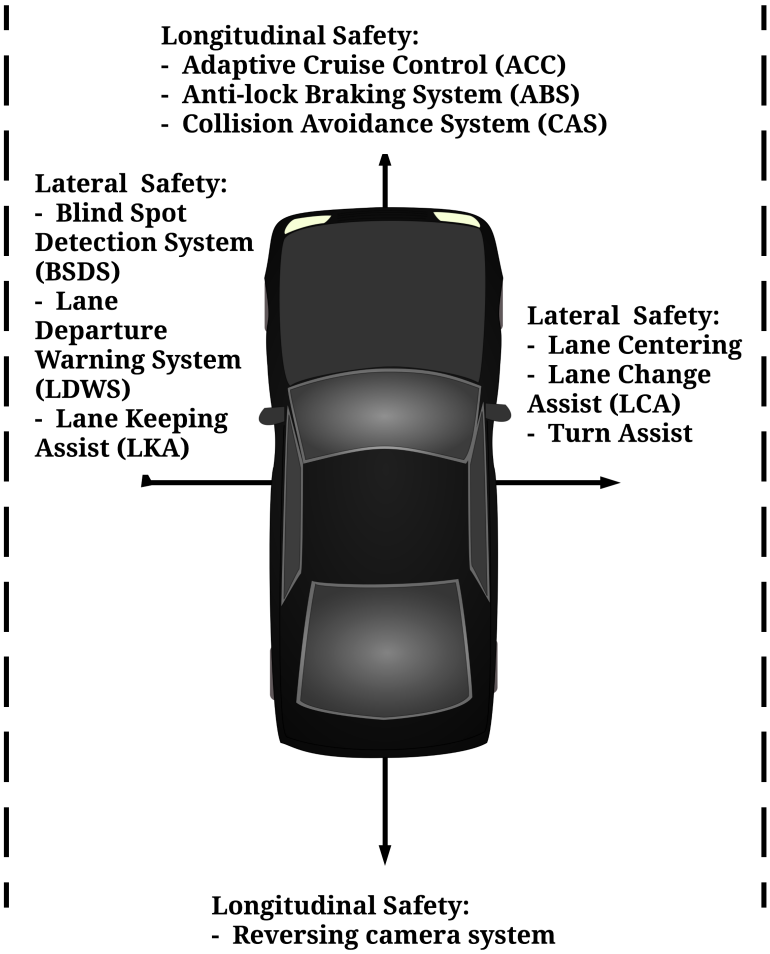


Figure 1. Lane departure warning and lane keeping assist positioned among the lateral and longitudinal advanced driver assistance system (ADAS) functions of a typical production vehicle. Abbreviations: ADAS, advanced driver assistance system.

Lane detection, the computer vision problem underlying LDWS, has undergone two major methodological shifts since it was first studied in the 1990s. Early systems relied on hand engineered image features, such as edge operators, colour thresholds, and Hough transform voting, combined with a geometric model of the lane fitted to those features [2,6–8]. Beginning around 2017, convolutional neural networks (CNNs) trained end to end on large labelled datasets displaced hand-engineered pipelines, first through pixel-wise segmentation and later through anchor, keypoint, and curve parameterised detection heads that run in real time [9–11]. Most recently, transformer architectures operating in bird's eye view (BEV) or in three-dimensional space have extended lane detection into a form suitable for the multi-camera, high definition (HD) mapping pipelines used in current production systems [12–14]. Each shift was accompanied by an expansion of public benchmark datasets and a rise in published output. Driver assistance functions such as these rely on sensors, and Figure 2 summarises the market drivers, challenges, and trends behind their development.

Earlier reviews of this field fall into three groups, compared in Table 1. The first group, published before or at the start of the deep learning era, treats lane detection as one part of a driver assistance system. McCall and Trivedi [2] (2006) surveyed lane position detection and tracking alongside their own VioLET system and its evaluation, and noted that departure warning requires a time-to-lane-crossing forecast. Bar Hillel et al. [15] (2014) decomposed

road and lane perception into functional modules, including temporal integration, and discussed the false alarm requirements of warning applications. Narote et al. [16] (2018) gave a fuller account than the other reviews in this group, with dedicated sections on lane detection, lane tracking, and lane departure warning, including guard zones and time to lane crossing, but without lane keeping control or test standards. Xing et al. [17] (2018) reviewed detection algorithms, their integration with other sensors and vehicle systems, and evaluation methods. Chen et al. [18] (2020) described commercial LDWS and their departure decision rules, then reviewed image processing and semantic segmentation methods for lane line detection. Waykole, Shiwakoti, and Stasinopoulos [19] (2021) reviewed detection and tracking algorithms, including model predictive lateral control for lane keeping, with a qualitative comparison of reported results.

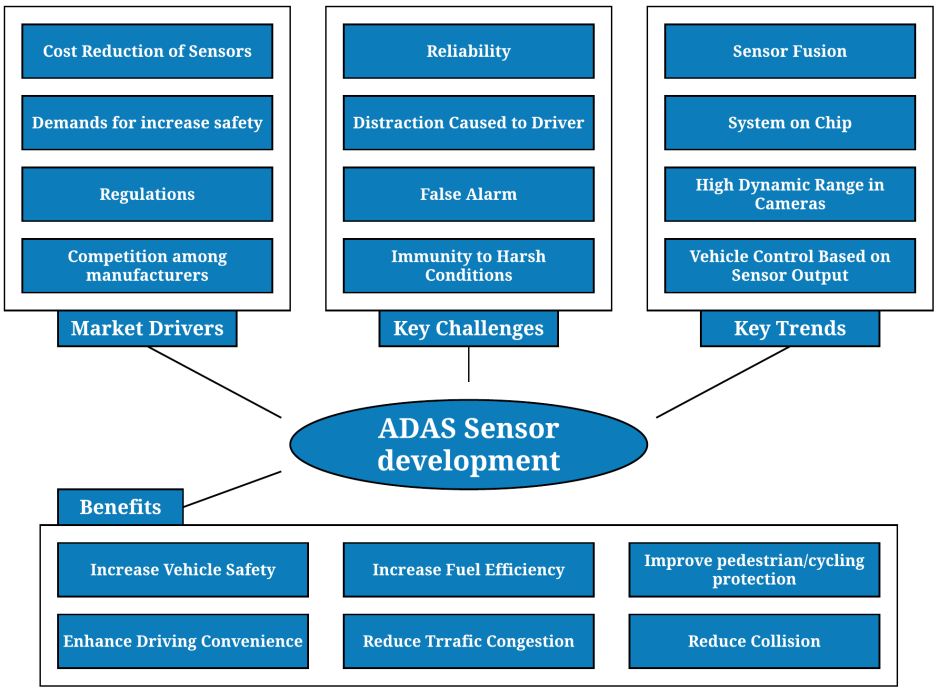


Figure 2. Market drivers, key challenges, key trends, and benefits associated with advanced driver assistance sensor development, of which lane departure warning is one instance.

The second group documents the deep learning era of detection. Zhang et al. [20] (2022) catalogued deep learning based lane marking detection as a line of work separate from the classical era, and Al Mamun et al. [21] (2022), a review coauthored by the present author, organised the same literature by network architecture and loss function and compared reported TuSimple results. Tang, Li, and Liu [22] (2021) organised it by network type, loss function, and pre and post processing, also compared reported TuSimple accuracy, and treated temporal information only through a few multi-frame networks. He et al. [23] review monocular lane detection architectures spanning two-dimensional and three-dimensional formulations. Bi et al. [24], Teng et al. [25], and Luo et al. [26] each survey the same detection problem with attention to benchmark datasets, evaluation protocol, and open technical challenges, and Ma et al. [27] narrow the same exercise to monocular three-dimensional lane detection. Gamerdinger et al. [28] focus on the datasets used to compare detection methods, and Sun, Kong, and Paek [29] (2025) organise camera, light detection and ranging (LiDAR), and fusion-based detection by processing stage. Kou et al. [30] (2026) give a further comprehensive review of lane detection, Grün [31] (2026) surveys the public lane detection datasets and how well their annotations support

driving tasks, and Keatmanee et al. [32] (2018) survey vision-based lane marking detection and tracking. Zakaria et al. [33] (2023) differ in method: they followed PRISMA and screened 435 records down to 102 included studies published from 2018 to 2021, but they also cover detection alone. These reviews give quantitative benchmark comparisons and detailed accounts of datasets and metrics, but each is limited to detection. Tracking appears in them only as temporal fusion inside detection networks, and warning decision logic and steering control are not reviewed. The third group addresses standards rather than methods: Wang et al. [34] (2025) review global LKA regulatory frameworks, including China's recommended national standards (GB/T), United Nations (UN) Regulation No. 79 [35], and the European New Car Assessment Programme (Euro NCAP). They summarise the perception, decision, and execution chain at the level of detail needed for standards compliance, including the lateral control strategies that the standards constrain: proportional integral derivative (PID), preview, and model predictive control, in six pages and ten references. Their review surveys regulatory harmonisation across jurisdictions rather than the technical literature on each pipeline stage. Wei, Pfeffer, and Edelmann [36] (2024) review how lane keeping assistance systems are assessed, through objective metrics, subjective test drives, and methods that link the two, and compare the lane keeping tests of International Organization for Standardization (ISO) standard 11270 [37], UN Regulation No. 79, and Euro NCAP. They describe departure detection only through time and distance to line crossing and do not review detection methods. Qin et al. [38] (2021) give an overview of lane-keeping assistance based on human-machine cooperative control.

Table 1. Coverage of earlier reviews of lane detection and lane departure warning, by pipeline stage and topic. Y, dedicated section or substantial treatment; P, brief or incidental treatment; –, not covered.

Review	Year	Detection	Tracking	Warning Logic	Steering Control	Test Standards	Benchmark Comparison	Mixed Traffic
McCall and Trivedi [2]	2006	Y	Y	P	P	–	P	–
Bar Hillel et al. [15]	2014	Y	Y	P	P	–	–	–
Narote et al. [16]	2018	Y	Y	Y	–	–	P	P
Xing et al. [17]	2018	Y	P	P	P	–	–	–
Chen et al. [18]	2020	Y	P	P	P	–	P	–
Waykole et al. [19]	2021	Y	P	P	Y	–	P	–
Tang et al. [22]	2021	Y	P	–	–	–	Y	–
Zhang et al. [20]	2022	Y	P	–	–	–	Y	–
Al Mamun et al. [21]	2022	Y	P	–	–	–	Y	–
Zakaria et al. [33]	2023	Y	P	–	–	–	–	P
He et al. [23]	2024	Y	P	–	–	–	Y	–
Wei et al. [36]	2024	–	–	P	Y	Y	–	–
Bi et al. [24]	2025	Y	P	–	–	P	Y	–
Luo et al. [26]	2025	Y	P	–	–	–	Y	–
Ma et al. [27]	2025	Y	P	–	–	–	Y	–
Gamerdinger et al. [28]	2025	P	–	–	–	–	–	–
Sun et al. [29]	2025	Y	P	–	–	–	Y	–
Wang et al. [34]	2025	P	–	–	Y	Y	–	–
Teng et al. [25]	2026	Y	P	–	–	–	Y	–
This review	2026	Y	Y	Y	Y	Y	Y	Y

Table 1 shows the resulting gap. Each stage of the pipeline has been reviewed somewhere, but not together and not at the current state of the art. Apart from Wang et al. and Wei et al., who review standards and assessment rather than methods, the reviews that treat warning logic or steering control in any depth predate, or barely reach, deep learning-based detection, and the recent reviews cover detection alone. These two are also the only reviews that name a specific test procedure, such as ISO 17361 [39], UN Regulation No. 79, or the

National Highway Traffic Safety Administration (NHTSA) and Euro NCAP protocols; Bi et al. refer to standards only in general terms. Wang et al. do not cover ISO 17361 or the NHTSA procedure and treat lane detection in a single subsection. Wei et al. review the assessment of lane-keeping assistance but not the detection, tracking, or warning methods that feed it. Mixed traffic and Southeast Asian conditions appear only in passing in Narote et al.'s mention of Indian road data and Zakaria et al.'s note on Malaysian data collection and monsoon rain. The present review covers all four stages using the literature published since 2018, compares reported results where common metrics exist, and relates them to the current test procedures. A review focused only on detection accuracy leaves open how improvements in detection translate into a system that warns or intervenes reliably, which largely determines whether an LDWS delivers the safety benefits described above once deployed at scale.

This paper addresses that gap. Its contributions are as follows.

1. A review of the complete LDWS pipeline (detection, tracking, warning decision logic, and steering intervention), rather than the detection subproblem alone, using the literature published since 2018; Table 1 compares this scope with earlier reviews.
2. A structured account of lane detection spanning three methodological eras (classical feature and model-based methods, two-dimensional deep learning methods, and three-dimensional, bird's eye view, and transformer-based methods), together with a quantitative comparison of reported benchmark performance across TuSimple, CULane, BDD100K, and OpenLane.
3. A summary of current regulatory test requirements, including NHTSA's November 2024 lane keeping assist and lane departure warning confirmation test procedure [40], which partly addresses the lack of an established evaluation protocol, identified as an open problem in earlier lane detection literature.
4. The identification of a research gap, separate from the synthesis in contributions 1 to 3 and supported by traffic, road marking, and method performance evidence from Malaysia. Mixed traffic with a high share of motorcycles, worn or missing lane markings, and monsoon rain, all characteristic of Southeast Asian roads, remain underrepresented in the lane detection literature and its benchmarks, which come mainly from structured roads in North America, Europe, and East Asia. Section 9.2 sets out this evidence and the requirements for a benchmark that would close the gap.

The remainder of this paper is organised as follows. Section 2 provides background on the advanced driver assistance system context in which LDWS operates. Section 3 reviews lane detection across the three methodological eras introduced above. Section 4 reviews the datasets and evaluation metrics used to compare detection methods, and Section 5 presents a quantitative benchmark comparison across representative methods from each era. Sections 6–8 review lane tracking, lane departure warning decision logic with the current regulatory test procedure, and steering intervention, respectively. Section 9 discusses open challenges and future directions, and Section 10 concludes the paper.

1.1. Review Methodology

This review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 statement [41]. The review protocol was not registered in advance, and the completed PRISMA 2020 checklist is provided in the Supplementary Materials. The review questions were: which methods have been proposed for each stage of the LDWS pipeline since 2018 (RQ1); how each stage is evaluated, with which metrics and datasets, and how comparable the reported results are (RQ2); how regulatory test procedures relate to the metrics used in research (RQ3); and which gaps remain across the pipeline (RQ4).

Information sources and search.

Two databases were searched: OpenAlex, an open index of scholarly works, on 15 October 2026, and IEEE Xplore, which indexes the IEEE journals and conferences where much of this literature appears, on 16 October 2026. Both were searched for journal articles and conference papers published from January 2018 to the search date. Five searches were run in each database: one for each pipeline stage, lane detection (D), lane tracking (T), warning decision logic (W), and steering intervention (S), and one for earlier reviews (R), which supplied Table 1 and was not limited by date. The lane detection search was restricted to studies whose title or abstract names a public benchmark, since the detection synthesis in Section 5 compares reported benchmark results. The steering intervention search was restricted mainly to titles, since the term lane-keeping in abstracts returns a large body of general vehicle control work. The full search strings are given in Appendix A (Table A1). Records were also identified by other methods: thirteen fixed queries in Consensus. Consensus is a relevance ranked search engine over Semantic Scholar, OpenAlex, and PubMed; it returns a fixed number of top results per query and therefore cannot provide a reproducible count. The regulatory documents of NHTSA, Euro NCAP, the United Nations, and ISO, the public datasets, and foundational work published before 2018 are cited for context but were not part of the systematic selection.

Eligibility criteria.

Studies were included if they proposed or evaluated a method for at least one pipeline stage for road vehicles (IC1); used camera input, alone or fused with other sensors, for detection and tracking, or any sensing for warning and steering (IC2); were peer-reviewed journal articles or conference papers (IC3); reported a quantitative evaluation on a benchmark, in simulation, on a test track, or on road (IC4); and were in English and published from January 2018 to the search date (IC5). Studies were excluded if they concerned vehicles other than road vehicles (EC1); treated lane detection or keeping as a minor component that was not evaluated separately (EC2); reported no quantitative evaluation (EC3); were duplicates or had been superseded by a more complete version (EC4); were not available in full text (EC5); were reviews or surveys, which were assessed separately for Table 1 (EC6); or were preprints that had not been peer reviewed (EC7).

Selection process.

Records were deduplicated by DOI and then by normalised title and year. Titles and abstracts were screened against the criteria above, with a reason code recorded for every record, and full texts of the remaining reports were assessed in the same way. Every exclusion and every uncertain record was reviewed with its stated reason, and a random sample of one in ten full text inclusions was rechecked. All final decisions were made by the author. Reports that could not be obtained through institutional subscriptions or open access sources were recorded as not retrieved. Of the 41 records found through Consensus, 9 had also been found by the database searches and were counted there. The flow of records is shown in Figure 3. The searches identified 2568 records, 1760 from OpenAlex and 808 from IEEE Xplore (by block: lane detection 827, lane tracking 531, warning 621, steering 462, earlier reviews 127). After 780 duplicates were removed, 1788 records were screened by title and abstract and 484 were excluded. Of the 1304 reports sought, 415 could not be retrieved, and 889 were assessed in full, of which 210 were excluded. Other methods contributed 16 further studies. In total, 695 studies were included: 442 on lane detection, 46 on lane tracking, 44 on warning decision logic, and 163 on steering intervention. Of the included studies, 105 were published in 2025 and 51 in 2026 up to the search date. These comprise 125 on lane detection, 21 on steering intervention, 8 on lane tracking, and 2 on warning decision logic.

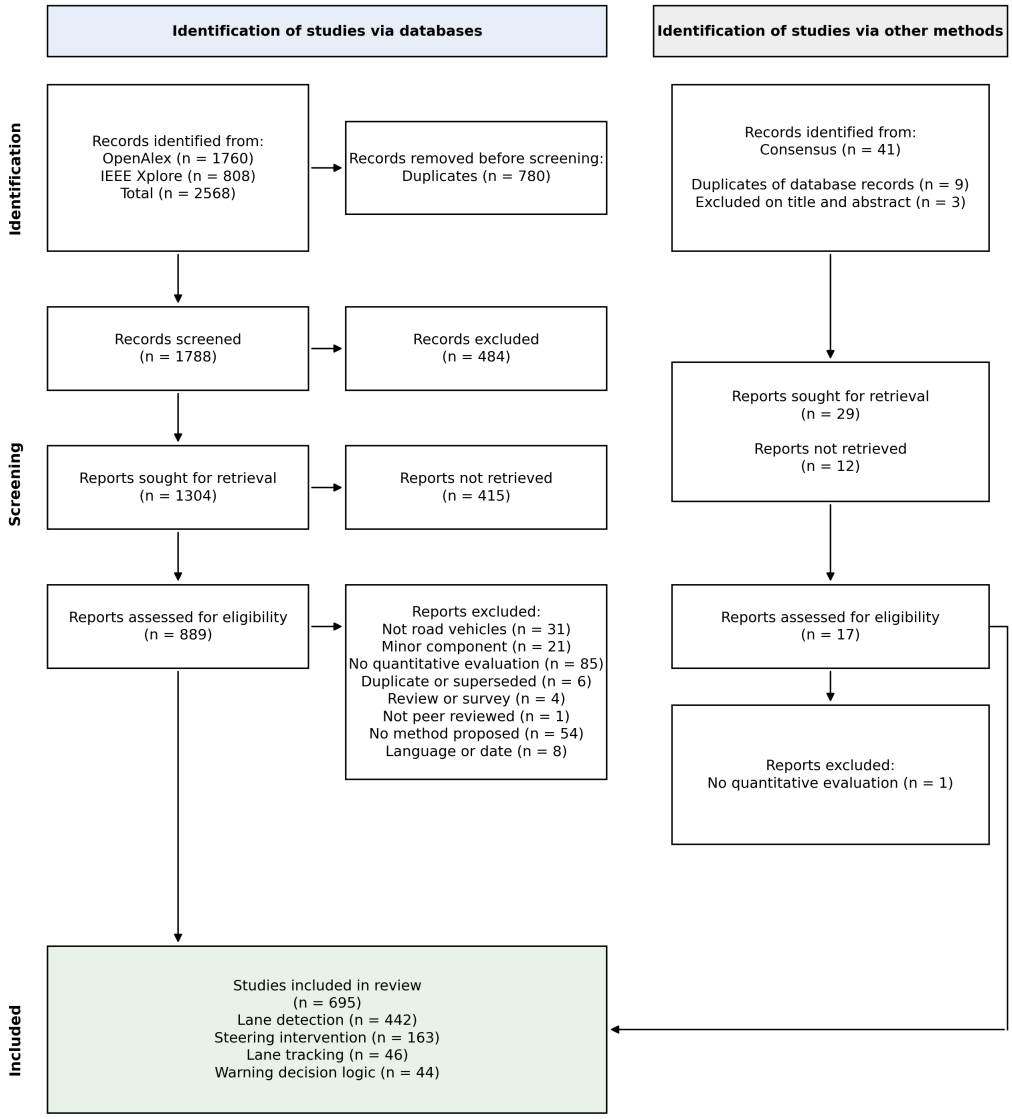


Figure 3. PRISMA 2020 flow diagram of the identification, screening, and inclusion of studies. Abbreviations: PRISMA, Preferred Reporting Items for Systematic Reviews and Meta-Analyses.

Table 2 summarises the included studies by pipeline stage.

Quality appraisal and data extraction.

Each included study was appraised on five items: whether the method is described in enough detail to reproduce it (Q1); whether the evaluation uses a public dataset, a standard test procedure, or a clearly described real vehicle test (Q2); whether the evaluation metric is defined (Q3); whether results are compared with at least one baseline (Q4); and whether hardware and runtime, or test conditions, are reported (Q5). Studies scoring three or more enter the quantitative comparison tables; studies scoring below three are cited descriptively only. For each study, the pipeline stage, method family, dataset, metric, reported result, hardware and runtime, sensing, and the region where the evaluation data were collected were extracted. The values reported in the comparison tables of Sections 5–8 were checked against the source papers.

Limitations of the method.

The search used OpenAlex and IEEE Xplore rather than broader subscription databases such as Scopus or Web of Science and was limited to English language publications, so

relevant work indexed elsewhere, or published in other languages, may be missed; the supplementary consensus queries were used to reduce this risk. Studies whose abstracts do not name a benchmark are not retrieved by the lane detection search; some widely used methods of this kind are discussed in Sections 3 and 5 from the earlier literature but are not counted among the included studies. Of the reports sought, 415 could not be obtained, most of them subscription papers; this may bias the included set towards open access work. Restricting the detection search to studies that report public benchmark results favours methods evaluated on those benchmarks, and the steering search, being limited to titles, may miss studies that describe lane keeping control only in the abstract. Final screening decisions were made by a single reviewer, the author, so no inter-rater agreement statistic between two reviewers is available. Reported results were extracted as published and were not reevaluated under common conditions (Section 5).

Table 2. Studies included in the review, by pipeline stage. Evaluation sources count studies, and a study may use more than one dataset. Quality is the five item score of Section 1.1; studies scoring 3 or more enter the quantitative comparison tables. The full list with the extracted data is given in Supplementary Table S1.

Stage	Studies	Since 2023	Score 3 or More	Main Evaluation Sources (Studies)	Main Method Families
Lane detection (Section 3)	442	263	421	TuSimple 250; CULane 203; BDD100K 50; OpenLane 34; Caltech 32; Apollo synthetic 26; no public benchmark 54	Segmentation; row and anchor classification; curve and keypoint regression; transformer; three-dimensional and BEV; classical
Lane tracking (Section 6)	46	23	43	TuSimple sequences 15; VIL-100 13; OpenLane-V 7; CULane 5; Caltech 4	Learned video and temporal networks; Bayesian filters and multiple target tracking
Warning (Section 7)	44	9	40	Recorded road video or images 20; naturalistic or fleet driving data 8; field or proving ground 7; driving simulator with drivers 6; simulation 3	TLC and lateral offset thresholds; learned departure and intent prediction; warning without a camera; warning timing studies
Steering (Section 8)	163	58	152	Numerical simulation 76; driving simulator with drivers 50; real vehicle 20; hardware in the loop bench 11; recorded driving data 6	Shared control; MPC; robust, fuzzy, and LPV control; sliding mode; learned and reinforcement learning controllers
Total	695	353	656		

Abbreviations: BEV, bird's eye view; LPV, linear parameter varying; MPC, model predictive control; TLC, time to lane crossing.

2. Background

This section places LDWS among the driver assistance functions, outlines the sensing modalities available for lane position estimation, and sets out the four-stage pipeline that structures the rest of the paper.

2.1. ADAS Taxonomy and the Position of LDWS

Advanced driver assistance systems (ADAS) are conventionally divided into longitudinal functions, such as adaptive cruise control and automatic emergency braking, and lateral functions, which govern the vehicle's position across the width of the road. LDWS and LKA belong to this second category, alongside blind spot detection and lane change assist, and Figure 1 situates them within that broader taxonomy. LDWS and LKA share their sensing and differ in authority: an LDWS alerts the driver through a visual, audible, or haptic signal and leaves the corrective action to the driver, while an LKA system applies

a corrective steering torque. Many production vehicles implement both on a shared lane detection and tracking pipeline; the two differ only in the final stage, reviewed in Section 8.

This taxonomy is long established. Takahashi and Asanuma [42] (2000) documented Honda's second phase Advanced Safety Vehicle programme, one of the earliest efforts to integrate camera- and radar-based lateral and longitudinal safety functions into a single vehicle platform under a Japanese Ministry of Transport research initiative. Shladover [43] (2007) reviewed twenty years of the California PATH programme's automated highway research, tracing the field's progression from lateral guidance embedded in the infrastructure towards camera-based sensing carried on the vehicle, which dominates the literature reviewed here. Moving an ADAS function from a research prototype into a mass-produced vehicle requires sustained interaction between manufacturers, regulators, and suppliers. As Section 7.2 shows, this process has only recently converged on a standardised confirmation test procedure for LDWS.

2.2. Sensing Modalities

The large majority of the literature reviewed in this paper, and most of Section 3, assumes a single forward-facing camera as the sensing modality. This is consistent with the well-documented shift towards look-ahead, camera-based sensing, which displaced earlier look-down schemes built into the infrastructure, such as magnets and electrified wires embedded along the highway, because it requires no modification to existing road infrastructure. Radar and LiDAR-based approaches, which appear briefly in Sections 3.3, 6 and 8 as points of comparison, are alternatives that sense lane or obstacle position without relying on visible light. They therefore do not depend on the lighting and marking visibility conditions that limit a purely camera-based system, but they carry a higher hardware cost. Xu [44] studies millimetre wave radar point clouds and proposes a dedicated methodology and workflow for extracting lane geometry from radar returns, rather than treating radar only as a supplement to the camera. Viswanathan and Hussein [45] (2017) survey the image processing and embedded hardware techniques common to camera-based systems. Even within the camera-based literature that this review focuses on, the computational budget of embedded automotive hardware is a first-order design constraint, and it recurs in the embedded and edge deployment methods reviewed in Section 3.2.

Where a second sensor is available, the fusion strategy chosen affects both accuracy and computational cost. Early fusion combines raw or lightly processed camera and radar or LiDAR data before any lane-specific inference runs. In principle it preserves the most information, but it requires the two sensor streams to be tightly synchronised in time and spatially calibrated against each other, a calibration burden that grows with vehicle age and vibration. Late fusion instead produces an independent lane or obstacle estimate from each modality and combines only the resulting estimates. It trades some of early fusion's theoretical accuracy ceiling for looser synchronisation requirements and the ability to fall back on a single modality if the other degrades or fails. Section 8 revisits the same sensor redundancy argument for LiDAR-based reinforcement learning (RL) control. The camera-only literature that this review otherwise surveys implicitly sets the fusion question aside, but Xu's [44] radar-only formulation and the fused camera and radar or camera and LiDAR systems it compares against illustrate that this design choice remains open in the wider sensing literature.

2.3. The LDWS Pipeline

A deployed LDWS or LKA system is a pipeline of four stages (Figure 4), and the structure of this review follows that pipeline. Lane detection, reviewed in Section 3, estimates the lane boundary position in a single frame or a short window of frames. Lane

tracking, reviewed in Section 6, propagates and smooths that estimate across a continuous driving sequence. Lane warning, reviewed in Section 7, converts the tracked position into a decision on whether and when to alert the driver, most commonly through some formulation of time to lane crossing, and then issues a visual, audible, or haptic alert. Steering intervention, reviewed in Section 8, applies an automated corrective steering action. This fourth stage exists only in LKA systems; a warning only LDWS ends at the warning stage. Sections 4 and 5, which review datasets and benchmark performance, apply to the detection stage, since it is the only stage with large, well established, standardised public benchmarks. Sections 6–8 each note this disparity for their own stage. Vehicle lateral dynamics, the physical model connecting a steering command to an actual change in vehicle heading and position, is treated here as background; Rajamani [46] (2012) provides a standard reference treatment, which underlies the classical control methods reviewed in Section 8.

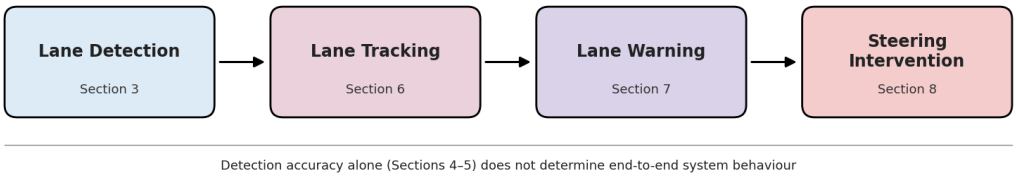


Figure 4. The four stage LDWS pipeline reviewed in this paper and the section reviewing each stage. Abbreviations: LDWS, lane departure warning system.

3. Lane Detection

Lane detection estimates the position and shape of lane boundaries from sensor data, most commonly a single forward-facing camera. This section reviews the three methodological eras introduced in Section 1, treating classical methods (Section 3.1) as historical context and the three-dimensional, bird's eye view, and transformer-based methods (Section 3.3) as the current state of the art.

3.1. Classical Feature and Model Based Methods

Classical lane detection methods are commonly divided into feature-based and model-based approaches [2], as Figure 5 illustrates. Feature-based methods localise the lane using low level image cues such as edges, colour, or intensity gradients, without an explicit geometric model of the road. Bertozzi and Broggi [6] developed GOLD, one of the earliest stereo vision-based systems, which remaps the image into a bird's eye view before extracting lane edges (Figure 6). This 1998 GOLD system refined an earlier version [47] that had already used the same bird's eye view remapping strategy two years earlier. Aly [48] combined oriented Gaussian filtering with random sample consensus line fitting and released the Caltech Lanes dataset with it as an early public benchmark (Figure 7). Broggi [49] addressed robust detection under heavy shadow, a narrower but persistent failure mode that continues to challenge purely camera-based systems. Labayrade et al. [50] ran three detection algorithms in parallel and fused their outputs for robustness against the failure of any single method.

The Hough transform is among the most widely reused feature-based techniques of this classical era. It maps edge points detected in image space into a parameter space in which collinear points, such as the straight lane segments typical of the near field road surface, reinforce each other into a detectable peak. Aung and Zaw [51] (2014) built a complete LDWS on this principle, applying Hough line detection to a region of interest ahead of the vehicle and triggering a warning once the detected lane position crosses a fixed threshold. Bhati and Somani [52] (2013) partitioned the transform's voting space to reduce the computational cost of a full image Hough transform. The Hough transform's straight

line assumption is also its principal weakness, since it matches curved lane geometry poorly; the model-based methods below address this.

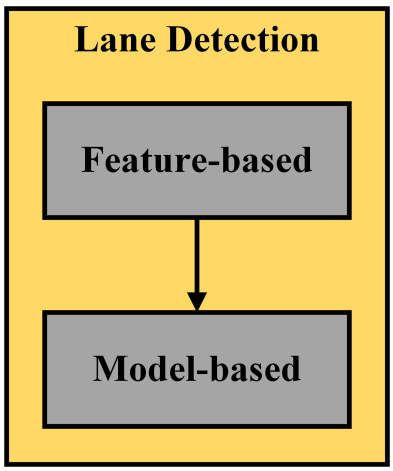


Figure 5. Classical lane detection methods are commonly divided into feature-based and model-based approaches.

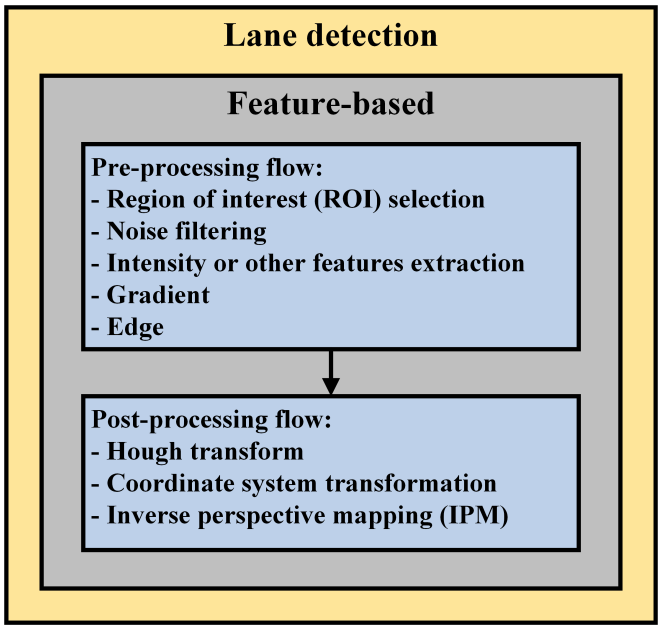


Figure 6. Representative processing flow of a feature-based lane detection pipeline, from preprocessing through postprocessing.

Model-based methods instead fit a geometric model, commonly a straight line, parabola, or spline, to the extracted lane features, trading flexibility on unusual road geometry for robustness to noise (Figure 8). Pomerleau's Rapidly Adapting Lateral Position Handler [7] (1995) and Kluge and Lakshmanan's deformable template method [8] (1995) are representative early examples. Wang, Teoh, and Shen [53] (2004) proposed a B-snake formulation that handles both straight and curved lanes within one deformable spline model. Borkar et al. [54] combined inverse perspective mapping (IPM), random sample consensus outlier rejection, and Kalman filtering in one pipeline, the typical composition of feature extraction, model fitting, and temporal smoothing in this era.

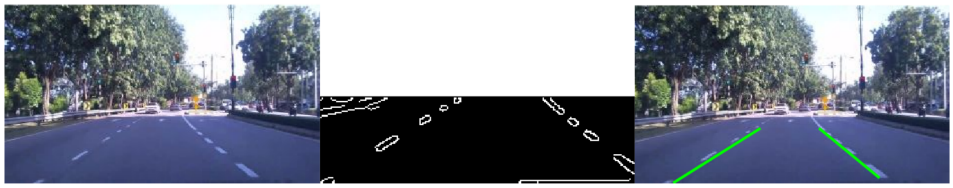


Figure 7. Example output of a classical feature-based pipeline: original image, extracted edge features, and detected lane boundaries overlaid on the original image.

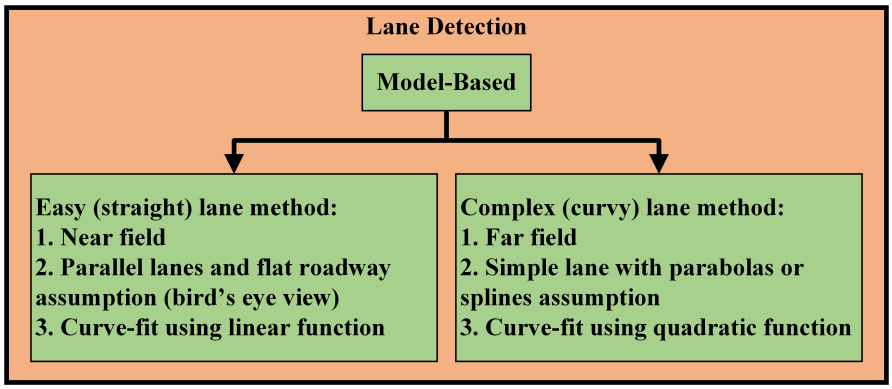


Figure 8. Classification of model-based lane detection methods by lane geometry complexity, distinguishing near-field, straight-line assumptions from far-field, curved lane models.

McCall and Trivedi's VioLET system [2] (2006) is one of the more thoroughly evaluated classical systems, reporting mean absolute error and standard deviation of lateral position across a wide range of lighting and lane marking conditions using a purpose-built test vehicle. These classical methods share two limitations relative to the deep learning methods reviewed next. First, hand engineered features generalise poorly to conditions the designer did not anticipate, in particular heavy shadow, faded markings, and unusual lane geometry (Figures 9 and 10). Second, evaluation was almost always conducted on small, privately collected datasets, which makes direct comparison between methods from this era unreliable.

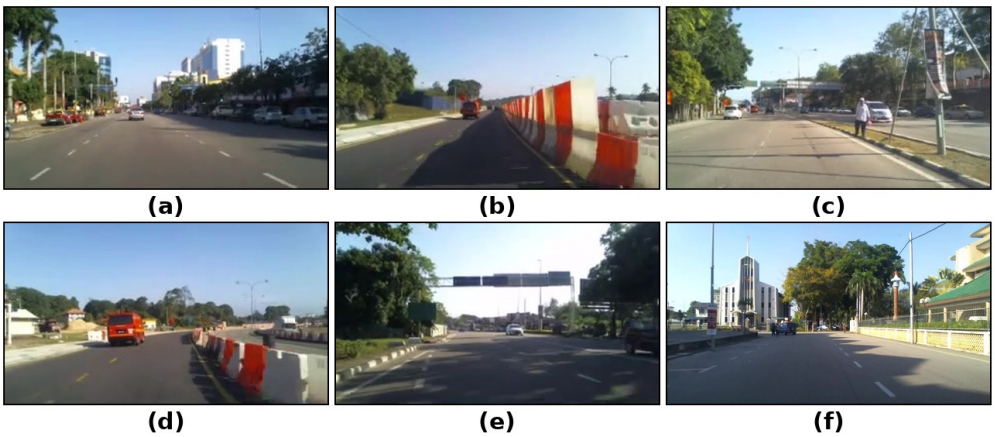


Figure 9. Examples of real-world driving conditions that challenge vision-based lane detection: clear structured road (**a**), roadworks with temporary barriers (**b**,**d**), a pedestrian near the carriageway (**c**), an overhead gantry sign structure (**e**), and an unmarked mixed-use campus road (**f**).



Figure 10. Daytime (**a**) and night time (**b**) driving conditions illustrating the lighting variation a lane detection system must tolerate.

3.2. Two Dimensional Deep Learning Methods

CNNs reframed lane detection as a learned pattern recognition problem, overtaking classical methods. Once large labelled datasets, TuSimple and CULane in particular, became available around 2017. Early networks, including Lee et al.'s Vanishing Point Guided Network [55] (2017), framed lane detection as semantic segmentation, classifying each pixel as a lane or not. This approach is accurate but expensive, and it relies on a postprocessing step to convert a pixel mask into discrete lane instances. Pan et al.'s spatial convolutional neural network (SCNN) [56] (2018) kept the segmentation formulation but passed messages slice by slice across the rows and columns of the feature map, so that information propagates along thin, elongated markings. SCNN was released together with the CULane benchmark reviewed in Section 4.

Row anchor methods reformulate lane detection as classification over a fixed set of horizontal rows, selecting the most likely lane position per row rather than classifying every pixel. Qin, Wang, and Li's Ultra Fast Structure Aware Deep Lane Detection (UFLD) [57] (2020) reported over 300 frames per second (fps) with this formulation and was later extended with a hybrid row and column anchor design for near vertical lanes [58]. Zheng et al.'s Recurrent Feature Shift Aggregator (RESA) [59] (2021) instead aggregated segmentation features recurrently to propagate context along thin, elongated markings. Abualsaud et al.'s LaneAF [60] (2021) addressed multi-lane instance separation within the same segmentation framework, predicting pixel-wise affinity fields that link each pixel to the correct lane instance without the fixed maximum lane count that row and column anchor methods assume. Anchor-based methods instead adapted line anchor representations from general object detection to lane geometry: Tabelini et al.'s LaneATT [9] (2021) added learned attention to aggregate global context per anchor, and Zheng et al.'s CLRNet [10] (2022) refined anchor predictions coarse to fine across feature pyramid levels, reporting state-of-the-art CULane accuracy at publication. Honda and Uchida's CLRerNet [61] (2024) revisited the training loss with an intersection over union metric better aligned with human perception of lane shape, improving on CLRNet's reported accuracy. Qi et al.'s CLRKD-Net [62] (2024) favoured inference speed over the further accuracy gains that CLRerNet pursued: it used knowledge distillation from a larger CLRNet teacher to train a smaller student network that keeps most of the accuracy while running faster. Xiao et al. [63] revisited the anchor representation, decomposing each anchor into separate angle and starting point predictions rather than regressing a single fixed line, reporting accuracy competitive with CLRNet on CULane. Xie et al. [64] instead reencoded row position through a learned positional embedding layer, and Su et al. [65] added a structural loss term that encourages predicted lanes to preserve pairwise geometric relationships, a lightweight way to add some of the topology awareness that conditional architectures address more directly.

A separate line of work modelled lanes as continuous curves rather than discrete anchors or pixels. Tabelini et al.'s PolyLaneNet [66] (2021) regressed polynomial coefficients directly, and Feng et al. [11] proposed a Bezier curve parameterisation that achieves competitive accuracy with far fewer parameters than segmentation or anchor-based de-

signs. Chen et al. [67] instead generated per-image dynamic convolution kernels through a transformer, so that the same architecture adapts its effective lane model to each scene. Wang et al.'s GANet [68] (2022) took a keypoint-based approach, regressing each keypoint to its lane's starting point in parallel rather than point by point, which improves inference speed. Xu et al. [69] proposed a relay chain formulation that predicts a lane as a sequence of connected local segments, propagating a running estimate outward from a starting point. The video tracking methods reviewed in Section 6 later echo this forward propagation logic. Liu et al.'s CondLaneNet [70] (2021) addressed a limitation common to the methods above, namely difficulty with complex topology such as forks and densely packed lanes, through a conditional convolution head that adapts to instance-specific structure. More recent work has continued to refine this anchor and transformer design space along several independent axes. Qiu et al. [71] inject prior knowledge of typical lane shape into a transformer's attention mechanism to reduce the training data such models otherwise require. Yang et al. [72] represent a lane as an anchor chain processed by a transformer rather than a single fixed anchor. Zhou and Zhou [73] predict a full lane set in a single one to several transformer pass rather than one anchor at a time. Zhou and Shao [74] apply a diffusion model to progressively refine an initially noisy lane estimate, and Zoljodi et al. [75] use contrastive learning across augmented views of the same scene to improve representation quality without additional labelled data.

A related family of methods performs lane detection jointly with other perception tasks within a single network to meet the real-time constraints of embedded automotive hardware. Liu et al. [76] (2024) survey the broader multitask environmental perception work in autonomous driving, of which the joint lane, object, and drivable area architectures below are one instance. Wu et al.'s YOLOP [77] (2022) combined object detection, drivable area segmentation, and lane detection in one You Only Look Once (YOLO)-based backbone at 23 fps on a Jetson TX2 platform. YOLOPv2 [78] (2022) and HybridNets [79], released in 2022 and published in 2025, followed with similar multitask designs but different efficiency trade-offs. Zhan et al.'s YOLOPX [80] (2024) later replaced YOLOP's anchor-based detection head with an anchor-free design while keeping the same three-task structure. Most recently, Abdullah et al.'s LC-YOLO [81] (2025) adapted YOLOv8 for lane intrusion detection, the decision-relevant output for a warning system, an example of a possible shift towards architectures designed around the downstream warning task rather than detection accuracy alone. Other work targets efficiency. Hosseini et al.'s ENet-21 [82] (2024) redesigns the backbone as an optimised lightweight convolutional network, and Li and Hou [83] (2025) use wavelet enhanced context modelling with adaptive sampling to keep computational cost low without a full architectural redesign. Both are relevant to the cost-sensitive embedded deployment scenario discussed in Section 9.4. Table 3 groups the two-dimensional methods of this section by representation. Kazerouni et al. [84] (2023) argue for a modular vision-based perception pipeline under the same real-time constraint, with separate, individually replaceable stages for detection, tracking, and lane estimation, rather than a single jointly trained backbone. This trades some of the efficiency of multitask designs for easier maintenance and component-level validation in a deployed vehicle.

Table 3. Representative two-dimensional lane detection methods grouped by representation, as reviewed in Section 3.2. Table 4 gives the corresponding three-dimensional methods.

Representation	Representative Methods	Key Idea
Pixel-wise segmentation	VPGNet [55] (2017), SCNN [56] (2018), LaneAF [60] (2021)	Classify each pixel as lane or not; needs postprocessing to separate lane instances, which LaneAF does with affinity fields

Table 3. *Cont.*

Representation	Representative Methods	Key Idea
Row or column anchor classification	UFLD [57] (2020), UFLDv2 [58] (2022)	Classify the most likely lane position in each row; very high frame rate
Recurrent feature aggregation	RESA [59] (2021)	Recurrent feature shift propagates context along thin markings
Line anchors with attention	LaneATT [9] (2021), CLRNet [10] (2022), CLRerNet [61] (2024)	Line anchor representation refined with learned attention or coarse-to-fine stages
Curve parameterisation	PolyLaneNet [66] (2021), BezierLaneNet [11] (2022)	Regress polynomial or Bezier curve coefficients directly
Keypoints	GANet [68] (2022)	Parallel regression of keypoints to their lane's starting point
Conditional, topology aware	CondLaneNet [70] (2021)	Conditional convolution head adapts to the topology of each instance (forks, dense lanes)
Joint multitask	YOLOP [77], YOLOPv2 [78] (2022), HybridNets [79] (2025), LC-YOLO [81] (2025)	Lane detection, object detection, and drivable area segmentation in one backbone

Abbreviations: SCNN, spatial convolutional neural network; UFLD, Ultra Fast Structure Aware Deep Lane Detection; YOLO, You Only Look Once.

3.3. Three Dimensional, Bird's Eye View, and Transformer-Based Methods

The methods reviewed in Section 3.2 operate on the two-dimensional image plane and generally assume a flat road surface when converting a detected lane into a real-world position, an assumption that breaks down on sloped, banked, or undulating roads. Three-dimensional lane detection instead predicts lane geometry directly in three-dimensional space. Garnett et al.'s 3D-LaneNet [85] (2019) was among the first end-to-end networks to address this from a single image. Guo et al.'s Gen-LaneNet [86] (2020) followed, decoupling feature extraction from geometry regression to improve generalisation beyond the synthetic training data that both relied on at the time. Chang et al. [87] revisit the same monocular setting and rethink how individual lane points are grouped into complete lanes under the complex, densely intersecting geometries that challenge earlier anchor-based three-dimensional methods. Yan et al. [88] released ONCE-3DLanes, built from real rather than synthetic driving data, together with a dedicated monocular baseline. This extends the real-world benchmarking argument that OpenLane makes (below) to a second independent dataset.

Chen et al.'s PersFormer [12] (2022) introduced a learnable perspective transformer replacing the fixed IPM used in most prior work, and released OpenLane with it, which its authors describe as the first large-scale three-dimensional lane benchmark built from real-world footage rather than simulation. OpenLane has since become the standard benchmark for this era, occupying the same position TuSimple and CULane hold for two-dimensional methods. Subsequent methods explored several architectural directions: Anchor3DLane [89] regresses three-dimensional anchors directly, avoiding information loss from projecting into a bird's eye view; LATR [90] dispenses with a bird's eye view representation, querying three-dimensional lane points from front-view features through a transformer decoder; and BEV-LaneDet [91] (2023) takes the opposite position, arguing that a deliberately simple bird's eye view projection matches more complex designs at lower computational cost, which bears on the real-time constraints under which a deployed LDWS operates.

In this era, lane detection has also converged with the broader bird's eye view perception literature developed for scene understanding in autonomous driving. Li et al.'s BEVFormer [13] (2022) builds a unified bird's eye view feature representation from multi-

camera input using deformable spatial and temporal attention. It is not lane specific, but later lane- and map-focused work has adopted it as a backbone. Li et al.'s HDMapNet [92] (2022) and Liao et al.'s MapTR [14] (2023) reframe lane detection as one output of online HD map construction, predicting lane centrelines as part of a broader vectorised map. MapTR regresses map elements end to end, in a manner comparable to detection transformer architectures. Wang et al.'s OpenLane-V2 [93] (2023) established topology reasoning between lanes and traffic elements as a separately evaluated task (Section 4). Sensor fusion is a further route to three-dimensional accuracy: Luo et al.'s M2-3DLaneNet [94] (2022) fuses camera and LiDAR features into a shared representation, and the same group's DV-3DLane [95] (2024) extends this with a dual-view design combining front view and bird's eye view features. Zheng et al. [96] instead address monocular ambiguity through time, exploiting how a lane's true three-dimensional shape becomes better constrained as the vehicle moves and observes it from multiple viewpoints across consecutive frames. Lyu et al. [97] distil depth priors from a separate monocular depth estimation model to improve three-dimensional accuracy without requiring LiDAR at inference time. Most recently, vision transformer architectures have targeted specific failure modes rather than general accuracy. For severe occlusion, Su et al. [98] embed lane slope and category priors in a vision transformer to reconstruct hidden markings, in a two-dimensional formulation. Bai et al.'s CurveFormer++ [99] infers three-dimensional lanes directly from front-view image features without a view transform, refining curve queries through curve cross attention and fusing them over time (Table 4).

Table 4. Representative three-dimensional, bird's eye view, and transformer-based lane detection methods grouped by representation, as reviewed in Section 3.3. Table 3 gives the corresponding two-dimensional methods.

Representation	Representative Methods	Key Idea
3D anchor regression	3D-LaneNet [85] (2019), Gen-LaneNet [86] (2020), Anchor3DLane [89] (2023), Anchor3DLane++ [100] (2025)	Regress 3D lane anchors directly; 3D-LaneNet and Gen-LaneNet regress them in a top view obtained by IPM, whereas Anchor3DLane and Anchor3DLane++ regress them from front view features without a BEV projection
Learnable perspective transform	PersFormer [12] (2022)	Learnable IPM replaces the fixed geometric transform; introduces the OpenLane benchmark
BEV free transformer decoder	LATR [90] (2023), CurveFormer++ [99] (2025)	Query 3D lane points directly from front view features, bypassing BEV construction
Simplified BEV projection	BEV-LaneDet [91] (2023)	Deliberately simple BEV projection matches complex designs at lower compute cost
General BEV backbone (adopted)	BEVFormer [13] (2022)	Spatiotemporal attention BEV feature backbone, not lane specific but widely reused
Online HD map construction	HDMapNet [92] (2022), MapTR [14] (2023)	Frame lane centrelines as one output of a broader vectorised map
Topology reasoning	OpenLane-V2 [93] (2023), TopoMLP [101] (2024)	Add lane to lane and lane-to-traffic element topology ground truth and reasoning heads
Multimodal fusion	M2-3DLaneNet [94] (2022), DV-3DLane [95] (2024)	Fuse camera and LiDAR features into a shared 3D or BEV representation

Abbreviations: BEV, bird's eye view; HD, high definition; IPM, inverse perspective mapping; LiDAR, light detection and ranging.

This progression, from a fixed geometric assumption to a learnable bird's eye view representation to architectures that bypass bird's eye view construction, reflects the same

tension between accuracy and computational cost that shaped the classical distinction between feature based and model based methods in Section 3.1.

4. Datasets and Evaluation Metrics

Each methodological era reviewed in Section 3 was enabled by, and evaluated against, a different generation of public benchmark datasets.

TuSimple, released in 2017, was one of the first widely adopted public lane detection benchmarks, consisting of highway driving footage collected in the United States under stable lighting and weather. It is scored using an accuracy metric defined as the fraction of correctly matched lane points within a fixed lateral tolerance, alongside separate false positive and false negative rates. Its narrow scope suited the early deep learning methods evaluated on it, but reported accuracy soon clustered near the ceiling, between about 93 and 97 percent for the representative methods in Section 5.1. The benchmark is now generally regarded as saturated [56,57].

CULane, introduced by Pan et al. [56] alongside the SCNN architecture, has since become the primary benchmark for two-dimensional lane detection. It contains urban and highway footage collected in Beijing, stratified into nine labelled scenario categories, including night, crowded traffic, no visible lane line, shadow, and curved road, which allows a method's accuracy to be reported and compared per scenario rather than only in aggregate. CULane is scored using F1, the harmonic mean of precision and recall, computed after treating each predicted lane as a fixed-width strip and applying an intersection over union threshold against the ground truth. Because CULane has not saturated in the way TuSimple has, aggregate CULane F1 is among the most frequently reported numbers in the two-dimensional lane detection literature and is the basis for the comparison in Section 5. Its principal limitation for this review is geographic: CULane's road markings, lane widths, and traffic density reflect Chinese urban and highway conditions.

BDD100K [102] is broader in scope than either TuSimple or CULane, spanning a wide range of weather conditions, times of day, and geographic locations across the United States. It provides object detection, drivable area segmentation, and lane detection annotations within the same clips. This multitask structure makes BDD100K the benchmark of choice for the joint detection architectures reviewed in Section 3.2, including YOLOP, YOLOPv2, and YOLOPX, which report lane and drivable area intersection over union from its labels. Fritsch, Kühnl, and Geiger's KITTI-Road benchmark [103] (2013) predates both TuSimple and CULane and proposed one of the first behaviour-based, rather than purely pixel level, performance measures, but its small scale means it has been largely superseded. Liu et al. [104] released a dedicated benchmark for road marking detection and classification on Chinese urban roads, addressing the recognition of marking types such as arrows, text, and zebra crossings rather than lane line geometry.

The three-dimensional era has its own benchmark, OpenLane, which was released with PersFormer (Section 3.3) and is derived from the Waymo Open Dataset. It is scored using an F-score over matched three-dimensional lane points, together with lateral and z-axis positional errors. Wang et al.'s OpenLane-V2 [93] (2023) extends OpenLane with ground truth for lane-to-lane and lane-to-traffic element topology, introducing an OpenLane-V2 Score (OLS) metric that combines detection accuracy with topology reasoning correctness; TopoMLP [101] reports a representative result on this metric.

Because each era adopted its own dataset and metric, reported accuracy figures are comparable within an era but not directly across eras. TuSimple's tolerance band accuracy, CULane's fixed-width intersection over union F1, and OpenLane's three-dimensional F-score each define a correct detection differently, and a method's ranking on one metric does not guarantee the same ranking on another.

None of the benchmarks reviewed above was collected in Southeast Asia or under the mixed traffic conditions common on Malaysian roads, where motorcycles and heavier vehicles share lanes with inconsistent adherence to markings. Two recent datasets narrow this gap without closing it. DriveIndia [105] is a 2025 object detection dataset covering over 120 hours and 3400 kilometres of diverse Indian driving with dense mixed traffic and heterogeneous infrastructure, though its annotation depth for lane-specific tasks has not yet been independently verified for LDWS use. IDD-3D [106], a 2023 extension of the Indian Driving Dataset, provides three-dimensional annotation for unstructured roads that frequently lack consistent lane markings. It is among the closest available public analogues to the mixed traffic conditions that this review identifies as underexplored. A separate strand addresses the same generalisation problem through domain adaptation rather than data collection. Stuhr, Haselberger, and Gebele's CARLANE [107] (2022) benchmarks unsupervised domain adaptation from simulation to real-world domains and finds that baseline methods still show substantially higher false positive and false negative rates than fully supervised training on matched data. Hu et al. [108] report a similar gap between simulated and real data for lane classification rather than detection alone. Bhardwaj et al. [109] target the same adaptation problem under a real-time constraint, which suggests that domain adaptation and embedded deployment cost are not independent design objectives. Lian et al. [110] approach generalisation from the training side instead, evaluating data augmentation strategies for their effect on the robustness of lane marking detection. Gamerdinger et al.'s SnowyLane [111] (2025) addresses a related generalisation axis, robustness on snow-covered rural roads where markings are physically absent, by using guard rails and road edges as detection cues instead. Public lane data from Malaysia are only now appearing [112,113], but to the author's knowledge, no Southeast Asian benchmark with a common protocol and published baselines yet exists (Section 9.2).

5. Quantitative Benchmark Comparison

This section compares reported performance across representative methods from Section 3, using the datasets and metrics introduced in Section 4. The figures are each paper's published results, not an independent reevaluation under common conditions. Even on the same benchmark, the methods differ in backbone network, input resolution, training schedule, and data augmentation, and in some cases in minor details of the train and test protocol. Inference speed is measured on different GPUs and with different software settings. In the papers reviewed here, changing only the backbone moves the CULane F1 of a single method by about one to two points (LaneATT [9] and CLRNet [10] each report several backbones), which is comparable to the gaps between successive methods in Table 5. The tables below therefore show broad trends only, and a difference of one or two points between two methods should not be read as evidence that one performs better under the same conditions.

5.1. Two Dimensional Methods on CULane and TuSimple

Table 5 lists reported CULane F1, in chronological order, for representative two-dimensional methods reviewed in Section 3.2. The progression shows a general but increasingly incremental improvement from 2021 to 2024: F1 rose by roughly five points between RESA (2021) and CLRNet (2022), but only about one further point from CLRNet to CLRerNet (2024). Chen et al.'s Sketch and Refine [114] (2024) reports a lower F1 than CLRerNet while prioritising inference speed. Within the limits stated above, this flattening is consistent with a benchmark approaching maturity, as TuSimple did several years earlier. It may be one reason why more recent work, reviewed in Section 3.3, has shifted towards three-dimensional and topology-aware formulations rather than further CULane

optimisation. The included studies published in 2025 and 2026 fit this pattern: several report a CULane F1 just above 80, for example, 81.02 for ProposalLaneNet with a DLA-34 backbone [115], 80.64 for FGNet [116], and 80.53 for StaBle-MambaNet [117], all below CLRerNet, while MPDDNet reports a higher 83.03 with a ResNet-34 backbone [118].

Table 5. Reported CULane F1 for representative two-dimensional lane detection methods, 2021 to 2024, as published (best reported variant).

Method	Year	CULane F1 (%)	Notes
LaneATT [9]	2021	77.02	Line anchors with learned attention
RESA [59]	2021	75.3	Recurrent feature shift aggregation
CondLaneNet [70]	2021	79.48	Conditional convolution, topology aware
GANet [68]	2022	79.63	Keypoints with global association
CLRNet [10]	2022	80.47	Coarse to fine cross layer refinement
CLRerNet [61]	2024	81.43	LaneIoU loss, refines CLRNet
Sketch and Refine [114]	2024	78.9	278 fps; prioritises speed over peak F1

Abbreviations: fps, frames per second; IoU, intersection over union.

Table 6 summarises reported TuSimple results. The methods report two different metrics: the TuSimple accuracy defined in Section 4, and F1. Because the two are defined differently, the table lists them in separate panels, and no comparison is made across panels. Of the four methods that report accuracy, three exceed 95 percent; the exception is PolyLaneNet at 93.36 percent. About one percentage point separates UFLD [57] from Xie et al. [64]. The two methods that report F1, He et al. [119] and GANet [68], both exceed 96 percent. These narrow margins are consistent with the saturation described in Section 4. Reported inference speed varies much more, from 35 frames per second for Xie et al. to over 300 frames per second for UFLD. However, each paper measured speed on its own hardware, so these figures indicate an order of magnitude rather than a ranking. With that caveat, the narrow spread in accuracy and the wide spread in speed are consistent with a benchmark near its ceiling.

Table 6. Reported TuSimple results and inference speed for representative two-dimensional methods, as published. Panel (a) lists methods that report TuSimple accuracy, and panel (b) methods that report F1. The two metrics are defined differently and are not compared across panels. Where a paper reports several backbones, the variant is given in brackets. Speeds were measured on each paper's own hardware.

Method	Year	TuSimple Result (%)	Reported Speed (fps)
(a) Methods reporting accuracy			
UFLD (ResNet-18) [57]	2020	95.87	over 300
PolyLaneNet [66]	2021	93.36	115
LaneATT (ResNet-34) [9]	2021	95.63	171
Xie et al. [64]	2022	96.93	35
(b) Methods reporting F1			
He et al. [119]	2021	96.81	248
GANet (small) [68]	2022	97.71	153

Abbreviations: fps, frames per second; UFLD, Ultra Fast Structure Aware Deep Lane Detection.

5.2. Three Dimensional and Topology Aware Methods on OpenLane

Comparison of three dimensional methods is less standardised than in the two dimensional case above. Most papers reviewed in Section 3.3 report improvement relative to the immediately preceding method rather than a common absolute figure. This reflects OpenLane's shorter history and continuing disagreement over the primary metric: F-score, lateral error, or, since OpenLane-V2, the combined OpenLane-V2 Score. Where a comparable difference is available, it can be large: Luo et al.'s DV-3DLane [95] (2024) reports an

11.2 point F1 improvement and a 53.5 percent reduction in positional error relative to the prior state-of-the-art on OpenLane, a considerably larger gain for a single paper than any reported in the two-dimensional CULane progression in Table 5. Anchor3DLane++ [100] reports state-of-the-art results on three separate three-dimensional benchmarks, OpenLane, ONCE-3DLanes, and ApolloSim. This suggests that the anchor-based, bird's eye view-free design direction introduced in Section 3.3 is still being refined, and that the field has not converged on a single dominant architecture.

Unlike CULane F1 for two-dimensional methods (Table 5), no common figure yet allows a table of comparable rigour for three-dimensional methods; Section 9 returns to this limitation. None of the figures in this section, on either benchmark, measures anything beyond single-frame or short-clip detection accuracy: they say nothing about how stably a detected lane is tracked across a full driving sequence, how a false detection translates into a false alarm rate for the driver, or how smoothly a warning becomes a steering correction. These questions are addressed in Sections 6, 7 and 8, respectively.

6. Lane Tracking

Detecting a lane independently in every frame discards information available from the immediately preceding frames. Lane tracking uses this temporal redundancy. It smooths noisy or momentarily missing detections, resolves ambiguity during brief occlusion by a leading vehicle or a shadow, and provides a stable lane position estimate for the warning decision logic reviewed in Section 7. This section treats tracking as a problem separate from detection: tracking takes a per-frame lane estimate, or a sequence of frames, as input and produces a temporally consistent lane position as output.

Classical lane tracking, consistent with the wider classical era reviewed in Section 3.1, relied on recursive Bayesian filtering. Apostoloff and Zelinsky [120] combined multiple visual cues (colour, edge, and texture) within a particle filter framework, so that the failure of any single cue did not immediately break tracking. Wang, Bai, and Fairhurst [121] (2008) applied the related condensation algorithm to maintain multiple simultaneous hypotheses about road shape rather than committing to a single estimate at each frame. Neither method has been benchmarked against the learned temporal fusion methods reviewed below; the video benchmarks needed did not exist when they were published. Sultana et al. [122] show that this filter-based approach is still being refined: their pipeline combines bilateral filtering, an optimised intensity threshold, and a geometric repositioning range tracking algorithm to address lighting, weather damage, occlusion, and confusing markings. They report robustness gains in each case without a learned temporal model.

The Kalman filter is the recursive Bayesian estimator on which most classical tracking methods build. A Kalman filter maintains a running estimate of lane position and its rate of change, predicts one time step forward using a simple motion model, and then corrects that prediction using the current frame's detection. The prediction and the new measurement are weighted by their uncertainty. This gives the Kalman filter two properties suited to lane tracking. First, it degrades gracefully when a single frame's detection is noisy or briefly missing, since the prediction step alone can carry the estimate forward for a short interval. Second, it is computationally cheap enough to run in real time on the embedded hardware that Section 2.2 identifies as a first-order constraint. Its limitation is the same constant motion assumption that underlies the time-to-lane-crossing calculation reviewed in Section 7.1: a Kalman filter tuned for gentle highway curvature can lag or overshoot on a sharper turn. This is part of why the learned, attention-based temporal fusion methods reviewed below were developed as an alternative.

The systematic search identified 46 lane tracking studies published since 2018 (Table 2). Many keep the filtering formulation above and differ mainly in what they track and on

what hardware. Lee and Moon [123] track line segments with a Kalman filter on a dual-core ARM processor and report that tracking raises the per-frame detection rate by 14.2 percent on average over 48 clips from the United States and Korea. Chen et al. [124] run one particle filter per boundary on temporal slice images, and Akbari et al. [125] treat each marking as a target in clutter with integrated probabilistic data association and run at 6.5 frames per second. Two studies from the same group model lanes as dependent extended targets with spatio-temporal Gaussian processes [126,127]. Embedded implementations are common among these studies: Hough candidates are clustered between frames and tracked at 40 ms per frame on an NI CompactRIO real-time controller [128], and an embedded warning system tracks four lines in Hough parameter space within 41.67 ms per frame on an ARM Cortex A8 [129]. Most of these studies are evaluated on the authors' own clips or on small subsets of Caltech and TuSimple, so their detection rates cannot be compared with each other.

A second group uses tracking to keep a lane estimate alive when the camera fails, since a warning cannot be issued for a lane that is not seen. Song et al. [130,131] predict the lane coefficients from ego motion during detection dropouts and report a maximum lateral offset error of 0.31 m over a simulated 14 s loss of detection, compared with 0.58 m for their earlier method. Kang et al. [132] predict the lane from a kinematic model during camera failures of up to 3 s injected into proving ground recordings and keep the lateral error below 0.15 m at 50 m ahead on a straight road. A confidence adaptive Kalman filter driven by an inertial unit holds lane-level localisation for up to 3 s without vision on urban highways in Iran [133]. Fusion with other sensors has the same purpose: Camarda et al. [134] fuse the outputs of a front camera and surround view cameras and lower the lateral error at 0 to 10 m on the right boundary from 0.142 m to 0.113 m on a French motorway, and Jeong et al. [135] mask vehicles tracked by camera and radar before extracting lanes in dense traffic.

Until recently, the lack of a public video benchmark was a major obstacle to evaluating learned temporal tracking methods on equal footing with the single-frame detection methods reviewed in Section 3. Zhang et al.'s VIL-100 [136] (2021) addresses this gap. It contains 100 videos and 10,000 frames of real traffic and was released with a baseline model that fuses the current frame's features with those of several preceding frames through attention, to resolve occlusion ambiguity that a single frame cannot. VIL-100 became a standard benchmark for video lane detection and was joined in 2023 by OpenLane-V (below).

Two recent methods build on VIL-100. Jin et al.'s Recursive Video Lane Detection (RVLD) [137] (2023) propagates a curve or state representation recursively from one frame to the next, rather than redetecting the lane independently in each frame and only smoothing the result afterwards. This is closer to the classical filtering formulation above than most learned video methods, and its authors reported state-of-the-art results on VIL-100 at release. Its main limitation is that the recurrent state can drift or accumulate error over a long driving sequence without an explicit reinitialisation mechanism. The classical Bayesian filters above are, by design, somewhat more resistant to this failure mode. Zhou et al.'s LaneTCA [138] (2025) takes a different architectural route to the same problem. It pairs an accumulative attention module, which builds long-term context across a whole driving journey, with a separate adjacent attention module, which passes short-term information from frame to frame. Its authors report new state-of-the-art results on both VIL-100 and OpenLane-V, although Table 7 shows methods published before and after it with equal or higher F1 on both.

The learned temporal studies fall into two groups by benchmark. Several segment lanes from short frame sequences with convolutional recurrent units [139–143]. They are evaluated on sequence versions of TuSimple, CULane, or LLAMAS that each paper builds

itself, or on the tvtLANE set, and they report pixel accuracy rather than the official TuSimple point accuracy. DRSTNet, built on the same kind of recurrent unit, is an exception and reports the standard CULane F1 [144]. The pixel accuracy figures of the other studies, often above 97 percent, therefore cannot be compared with the detection results in Section 5, although one of them compares its pixel accuracy with the official TuSimple results of other methods [143]. The second group evaluates video instance detection on VIL-100 and, since 2023, on OpenLane-V. OpenLane-V is a reannotated video version of OpenLane of about 90,000 frames, introduced with RVLD [137]; the RVLD paper also introduced flickering and missing rates as temporal metrics. Table 7 lists the results these studies report. An early example, TGC-Net, adds temporal and geometric consistency constraints to feature shift aggregation [145]. On VIL-100, F1 at an intersection over union of 0.5 has risen from 0.839 for the MMA-Net baseline [136] to 0.940 for SIGMA-Lane [146]. The stricter F1 at 0.8 lies between 0.58 and 0.63 for six of the ten methods that report it. For the same methods, OpenLane-V F1 at 0.5 is about 0.1 below the VIL-100 value, while F1 at 0.8 differs by less than 0.05. Eight of the thirteen methods report speed, on different GPUs, ranging from 12 frames per second for MLM-Net [147] to 228 for PolyLaneNet++ [148]. Jeon and Kim [149] have since extended OpenLane-V with 60,000 further frames.

Table 7. Video lane detection results on VIL-100 and OpenLane-V reported by the included studies, as published. F1 is given at intersection-over-union thresholds of 0.5 and 0.8. Speeds were measured on each paper's own GPU. –, not reported.

Method	Year	VIL-100				OpenLane-V		Speed
		mIoU	F1 0.5	F1 0.8	Acc.	F1 0.5	F1 0.8	
MMA-Net [136]	2021	0.705	0.839	0.458	0.910	–	–	–
Twin non local [150]	2022	–	–	–	0.923	–	–	–
TGC-Net [145]	2022	0.738	0.892	0.469	0.941	–	–	–
MLM-Net [147]	2023	0.753	0.904	0.624	0.945	–	–	12 fps (GPU not stated)
SFED-Former [151]	2023	0.815	0.913	0.725	0.951	–	–	–
RVLD [137]	2023	0.787	0.924	0.582	–	0.825	0.566	about 80 fps, RTX 3090
STADet [152]	2024	0.816	0.903	0.724	0.949	–	–	39 fps, RTX 3090
PolyLaneNet++ [148]	2024	–	–	–	0.931	–	–	228 fps, RTX 3060
OMR [153]	2024	0.774	0.936	–	–	0.836	–	about 105 fps
DiffLane [154]	2025	0.789	0.932	0.586	–	0.831	0.568	about 60 fps, RTX 4090
LaneTCA [138]	2025	0.796	0.933	0.621	–	0.822	0.574	–
PHNet [155]	2025	0.783	0.915	0.615	0.908	0.804	0.588	78 fps, RTX 2080Ti
SIGMA-Lane [146]	2026	0.801	0.940	0.595	0.956	0.838	0.591	97 fps end to end, RTX 4090

Abbreviations: Acc., accuracy; fps, frames per second; mIoU, mean intersection over union.

Lane tracking remains less standardised as a research problem than lane detection (Section 3). The public video benchmarks have existed only since 2021 (VIL-100) and 2023 (OpenLane-V), compared with CULane's near-decade of continuous use, and 13 of the 46 tracking studies identified by the systematic search report results on VIL-100 (Table 7). Table 8 summarises the tracking methods discussed in this section.

Table 8. Lane tracking methods reviewed in Section 6, from classical filtering to learned temporal fusion.

Method	Year	Approach	Benchmark
Apostoloff and Zelinsky [120]	2003	Particle filter on multiple visual cues	Own footage
Wang, Bai, and Fairhurst [121]	2008	Condensation with multiple road shape hypotheses	Own footage

Table 8. *Cont.*

Method	Year	Approach	Benchmark
MMA-Net, VIL-100 baseline [136]	2021	Attention-based fusion of multiple frames	VIL-100 (introduced)
Sultana et al. [122]	2023	Classical features with geometric repositioning range tracking	Own footage
RVLD (Jin et al.) [137]	2023	Recursive state propagation from frame to frame	VIL-100, OpenLane-V
LaneTCA (Zhou et al.) [138]	2025	Accumulative and adjacent attention	VIL-100, OpenLane-V

7. Lane Warning

7.1. Warning Decision Logic

Lane warning converts a tracked lane position into a decision: whether, and when, to alert the driver that an unintended departure is imminent. The central quantity in this literature is time to lane crossing (TLC), an estimate of how many seconds remain before the vehicle's current lateral position and heading would carry it across the lane boundary. Godthelp, Milgram, and Blaauw [156] (1984) introduced TLC as a time-based measure of driving strategy, and Lin and Ulsoy [157] (1995) later formalised its calculation and analysed its frequency distribution. TLC assumes that velocity and heading remain constant over the prediction window. This assumption is also its main limitation, and much of the later literature can be read as attempts to relax it or to compensate for the false alarms it produces when it fails. Kwon and Lee [158] compared several decision strategies under the embedded hardware constraints of the time, and Dahmani et al. [159] (2013) proposed a Takagi Sugeno fuzzy observer to estimate road curvature, which reduces the false alarms that curvature misestimation causes in a constant heading TLC calculation. The observer was validated only in CarSim simulation, not on real roads.

False alarm rate, more than detection accuracy alone, weighs heavily in driver acceptance, since drivers tend to disable or ignore a system that warns too often, whatever its detection quality. Gao, Yin, and Zhang's [160] 2020 method combines a residual network, an online extreme learning machine (ELM), and an epsilon-greedy long short-term memory (LSTM) network to predict driver self-correction before a boundary is crossed. It reduces the false warning rate from 14.1 percent for a conventional TLC baseline to 1.2 percent, with a 98.8 percent correct warning rate. The result shows that learned warning logic that models driver behaviour can outperform the constant heading TLC assumption on the false alarms that this assumption produces. Jin et al.'s [161] 2024 method pursues the same goal with a bidirectional LSTM (BiLSTM) that evaluates two horizontal zones around the lane boundary. It incorporates individual driving characteristics rather than applying one fixed threshold to every driver.

For warning, the systematic search identified 44 studies (Table 2). This group is older than the detection group: 35 of the 44 were published from 2018 to 2022 and only 9 since 2023, whereas 263 of the 442 detection studies date from 2023 or later. Nineteen of the 44 apply a threshold to TLC, lateral offset, or lane line slope computed from a camera. Most of these are evaluated on recorded video with a departure detection rate per frame or per event, often on the authors' own clips without a baseline. Reported results range from a departure detection rate of 78.63 percent by day and 83.73 percent by night on Malaysian urban and highway video [162], through a per-frame warning accuracy of 91.56 percent by day and 85.86 percent by night at 32 frames per second on a Jetson Orin Nano [163], to a departure rate of 99.1 percent on KITTI images with ideal markings and 95.2 percent with

non-ideal markings at 14.4 to 23.4 ms per image on a laptop [164]. Only some studies in this group report false warnings; MTSAN, for example, reports a 3.45 percent false alarm rate with a 98.31 percent detection rate on Taiwanese highway video in poor weather [165].

Thirteen studies learn the departure or the driver's intention from vehicle signals, and these supply most of the evidence on false warnings. Wang et al. [166] fit a personalised driver model to naturalistic data from ten drivers and report a 3.07 percent false warning rate at a 1 s horizon, with about half the warning frequency of a basic TLC rule (0.1404 against 0.2747). Two studies on fleet data from professional drivers in Sweden, Germany, and China compare learned predictors with the constant velocity TLC model: a neural network improves the true positive rate by 7 percent in relative terms and lowers the false positive rate by about 22 percent [167], and a linear regression matches the neural network up to a 1 s horizon with 96 rather than 5200 multiplications [168]. On the same kind of fleet data, adding driver gaze lowers false interventions, mainly at horizons of 1 to 2 s [169], and modelling the uncertainty of the prediction makes the decision more robust to inconsistent sensor data [170]. A related strand infers lane change intention so that an intended crossing does not trigger a warning: an ensemble BiLSTM reaches 96.1 percent accuracy 0.5 s before the manoeuvre [171], and an analysis of 1375 naturalistic lane changes finds TLC, yaw rate, and lateral acceleration to be weak features for recognising them [172].

Four studies make the warning decision without a forward camera on the vehicle, which is relevant where markings are worn or absent. A method that compares the heading from a standard Global Positioning System (GPS) receiver with road headings detected all of about 200 lane changes on Minnesota roads [173], and a later version that builds the reference heading from past trajectories gave no false alarm in more than 10 trips [174]. Other studies predict the departure from closed-loop vehicle dynamics [175] or detect it from roadside cameras and radar [176]. A fifth study evaluates a bioinspired warning and control model only on simulated vehicle positions in MATLAB Simulink [177].

Three driving simulator studies examine warning timing and reliability rather than the decision rule, and their results bear on how a decision rule should be tuned. Navarro et al. [178] show that false warnings lengthen the lateral excursion of the next correctly warned departure, from 4.31 s after a missed warning to 5.05 s after a false one. In a study of 80 drivers on a high-fidelity simulator, warnings shortened the steering response mainly when drivers were distracted, and early warnings gave no benefit to attentive drivers [179]. Another study of 80 drivers found that an early warning cut the median departure duration of cautious drivers from 3.0 s to 1.8 s but helped aggressive drivers less, and recommended timing adapted to driving style [180]. Four further studies test existing warning systems. Commercial systems on a light truck and a passenger car, tested on a proving ground in UN Regulation No. 130 [181] and Euro NCAP scenarios, gave no warning in about 10 percent of trials [182]. A camera-based system in PreScan still warned with 80 percent marking wear in dry daylight and failed at 90 percent, with the warning light stuck on. With 50 percent wear, any rain suppressed the warning [183]. Field tests of production lane-keeping systems with a driving robot found that each system intervened at a different distance from the line for left and right departures (0.29 m and 0.76 m for one of them) [184]. The only test in the included set on Southeast Asian roads applied a protocol adapted from Euro NCAP and the procedure of Japan's National Agency for Automotive Safety and Victims' Aid to a production car on a state road in Melaka, in dry conditions and with a rain simulator. Both the lane departure warning and LKA functions activated in every scenario, but the outcome was recorded as pass or fail without synchronised measurement [185]. Table 9 gathers the warning results that the included studies report.

Table 9. Warning results reported by included studies, grouped by evaluation source (as published). Metrics differ between rows and are not comparable across rows.

Study	Year	Data	Decision Logic	Reported Result
Recorded road video or images				
Em et al. [162]	2019	Melaka urban and highway, 69,964 frames	Lateral offset ratio threshold	Departure detection 78.63% day, 83.73% night
Lai et al. [165]	2021	Taiwan highway, poor weather	Polynomial lane fit, boundary rule	Detection 98.31%, false alarm 3.45%
Chen et al. [164]	2023	KITTI images	Lateral offset threshold	Departure rate 99.1% ideal, 95.2% non ideal markings
Qureshi et al. [163]	2026	Own road video, day, night, rain	Lateral position window	Per frame warning accuracy 91.56% day, 85.86% night, 97.09% rain
Naturalistic or fleet driving data				
Wang et al. [166]	2018	SPMD, 10 drivers	Personalised driver model with TLC	False warning rate 3.07% at 1 s
Dahl et al. [167]	2019	Fleet data, Sweden, Germany, China	Neural network	TPR +7%, FPR about −22% against TLC
Dahl et al. [168]	2022	Same fleet	Linear regression	Equal to neural network up to 1 s; 96 multiplications
Driving simulator with drivers				
Gao et al. [160]	2020	21 drivers	ResNet, ELM, LSTM intent	False warning rate 1.2% against 14.1% for TLC
Zhang et al. [180]	2024	80 drivers	Early or late offset threshold	Median departure duration 3.0 to 1.8 s (cautious drivers)
Field, proving ground, or virtual test				
Chowdhury et al. [174]	2021	I-35, Minnesota	GPS heading, no camera	All of more than 100 lane changes; no false alarm in more than 10 trips
Re et al. [182]	2021	Proving ground, UN R130, Euro NCAP	Commercial systems	No warning in about 10% of trials
Gaevskiy et al. [183]	2023	PreScan, ISO 17361 lane change	Built-in camera model	Warned at 80% marking wear; system failure at 90%
Mansor et al. [185]	2020	State road, Melaka, dry and simulated rain	Production LDW and LKA	Activated in all scenarios (pass or fail only)

Abbreviations: ELM, extreme learning machine; FPR, false positive rate; GPS, Global Positioning System; LDW, lane departure warning; LKA, lane keeping assist; LSTM, long short term memory; SPMD, Safety Pilot Model Deployment; TLC, time to lane crossing; TPR, true positive rate.

Alongside the false alarm literature, a separate strand continues to refine the geometric estimation that feeds the warning decision. Luo et al.'s [186] 2022 method estimates yaw angle and lateral distance from only one of the two lane markings, which is useful when one marking is degraded or absent. It reports 98.95 percent average detection accuracy with a calibration strategy that the authors describe as readily deployable. Zhang, Sun, and Shu [187] address the related lane change warning problem. An improved Mask R-CNN, with anchor ratios derived from K-means++ clustering, feeds a lane change warning algorithm at 94.5 percent detection accuracy. Anbalagan et al.'s [188] 2023 vision-based system follows the same pipeline from detection to warning. It uses generative adversarial and recurrent networks to reconstruct occluded lane markings before issuing a warning, and reports 98.2 percent detection and 96.5 percent departure warning accuracy. More recently, Jeong et al. [189] (2024) look at warning reliability from the side of the road infrastructure.

They quantify how the retroreflectivity of physical road markings degrades under weather exposure and wear, and how that degradation reduces the LDWS recognition rate. They also propose a cost-effectiveness simulation framework for road marking maintenance policy.

Wang and Zhou's LKAlert [190] (2025) is the most recent architectural change in this section. LKAlert is a supervisory layer built on a vision-language model (VLM). It forecasts an LKA failure one to three seconds in advance and issues both a predictive alert and a natural language explanation, using surrogate lane segmentation features to guide attention. Its authors report 69.8 percent failure prediction accuracy and a 58.6 percent F1 score at approximately 2 Hz. LKAlert explains, rather than corrects, the failures of the underlying system (Table 10).

Table 10. Lane warning decision logic methods reviewed in Section 7.1, with reported accuracy or false alarm results as published.

Method	Year	Approach	Reported Result
Godthelp, Milgram, and Blaauw [156]	1984	TLC introduced as a time-based measure of driving strategy	Not applicable
Lin and Ulsoy [157]	1995	TLC calculation and frequency distribution	Not applicable
Dahmani et al. [159]	2013	Takagi Sugeno fuzzy observer of road curvature	Validated in simulation only (CarSim)
Gao, Yin, and Zhang [160]	2020	Residual network, ELM, and epsilon greedy LSTM predicting driver correction	Correct warning rate 98.8%; false warning rate 1.2%, against 14.1% for TLC
Luo et al. [186]	2022	Yaw and lateral estimation from a single lane marking	Average departure detection accuracy 98.95%
Zhang, Sun, and Shu [187]	2022	Mask R-CNN with K-means++ anchors; lane change warning	Lane change detection accuracy 94.5%
Jin et al. [161]	2024	BiLSTM predicting self-correction in two zones, with individual driving characteristics	False alarm rate 3.97%; prediction accuracy about 41% higher than DSPLS (simulator, 57 drivers)
LKAlert (Wang and Zhou) [190]	2025	VLM predictive alert with explanation	Accuracy 69.8%, F1 58.6%, about 2 Hz

Abbreviations: BiLSTM, bidirectional long short-term memory; DSPLS, directional sequence of piecewise lateral slopes; ELM, extreme learning machine; LSTM, long short-term memory; R-CNN, region-based convolutional neural network; TLC, time to lane crossing; VLM, vision-language model.

7.2. Regulatory Test Procedures

ISO first published ISO 17361 [191] in 2007, specifying performance requirements and a test procedure for LDWS nearly two decades before NHTSA's and Euro NCAP's current protocols, and issued the current edition in 2017 [39]. ISO 17361 has continued to inform later national and regional test procedures. However, its first edition predates the deep learning era reviewed in Section 3 and was written for the classical, feature-based detection systems of its time, so the standard does not by itself resolve the more recent gap that this section describes.

NHTSA's New Car Assessment Program published a lane-keeping assist and lane departure warning confirmation test procedure in November 2024 [40]. It sets out a test matrix of drift speed, roadway marking style, and departure direction that a vehicle's LKA and lane departure warning (LDW) systems must satisfy for confirmation under the United States NCAP. Euro NCAP's Lane Support Systems (LSS) test protocol [192], at version 4.3 as of December 2023, codifies a comparable scoring methodology for the European market. Together, these two procedures address the earlier absence of an established

evaluation protocol: an LDWS or LKA system intended for either market can now be evaluated against a standardised, publicly documented procedure rather than an ad hoc, manufacturer specific protocol. The same November 2024 NCAP decision [193] also added blind spot warning, blind spot intervention, and pedestrian automatic emergency braking, which suggests that standardised confirmation testing is extending across ADAS functions beyond LDWS and LKA (Table 11).

Table 11. Comparison of the two current LDWS and LKA regulatory confirmation test procedures reviewed in Section 7.2.

Aspect	NHTSA LKA and LDW Confirmation Test (November 2024) [40]	Euro NCAP LSS Test Protocol, Version 4.3 (December 2023) [192]
Market	United States (US NCAP)	Europe (Euro NCAP)
Scope	Lane-keeping assist and lane departure warning confirmation test	Lane Support Systems test and scoring methodology
Test matrix basis	Drift speed, roadway marking style, departure direction	Scoring defined by the protocol across lane support functions
Status at the search date (October 2026)	Current (published November 2024)	Current (version 4.3, published December 2023)

Abbreviations: LDW, lane departure warning; LKA, lane keeping assist; LSS, Lane Support Systems; NCAP, New Car Assessment Programme; NHTSA, National Highway Traffic Safety Administration; US, United States.

Table 12 sets the conditions and pass criteria of these procedures, alongside the metrics that the research literature reports for each pipeline stage. There are three differences. First, the procedures test lane detection only on clear, standard markings in good visibility. ISO 17361 excludes temporary and irregular markings such as roadwork zones [39], and its 2007 edition requires a horizontal visibility above 1 km [191]. Euro NCAP tests in daylight above 2000 lux without precipitation, on lanes 3.5 to 3.7 m wide marked to UN Regulation No. 130 [192]. The detection benchmarks of Sections 4 and 5, by contrast, deliberately include night, rain, shadow, and crowded scenes. NHTSA's procedure adds raised pavement markers [193], a marking type that the public benchmarks rarely contain. Second, every procedure judges a warning by where it occurs relative to the line: in the NHTSA test, the warning must come before the lane departure exceeds 0.3 m, at lateral velocities of 0.2 to 0.6 m/s and 72.4 km/h, and the 2007 edition of ISO 17361 sets the latest warning line 0.3 m outside the lane boundary for passenger cars [191]. The warning studies of Section 7.1 mostly report detection rates per frame or per event on recorded video, which cannot be converted into a warning position. Third, the steering procedures measure the lateral position after the intervention on a test track at one speed: Euro NCAP records the distance to the lane edge at 72 km/h, ISO 11270 limits the maximum offset to 0.4 m for light vehicles, and UN Regulation No. 79 adds a limit of 5 m/s^3 on the half-second moving average of lateral jerk [36]. Most steering studies in Section 8 report root mean square (RMS) or maximum lateral error in simulation, and few report distance to the lane edge or jerk. Only a few included studies evaluate against a published procedure: commercial warning systems tested on a proving ground in UN Regulation No. 130 and Euro NCAP scenarios [182], a warning system for a light commercial vehicle tested to ISO 17361 and UN Regulation No. 130 in simulation and on a test site [194], an ISO 17361 lane change scenario in PreScan [183], an end-to-end lane-keeping system driven on a proving ground that meets ISO 11270 requirements [195], lane keeping by model predictive control in a Euro NCAP lane support scenario [196], production lane departure prevention systems

tested in induced drifts at 80.5 km/h and judged against a threshold derived from the NHTSA criteria [197], and a test protocol adapted to Southeast Asian roads in Melaka [185]. Reporting the warning position and the lateral position after intervention, at the lateral velocities these procedures use, would allow research results to be compared with the regulatory pass criteria.

Table 12. Conditions and pass criteria of the current test procedures, set against the metrics reported in the research literature, by pipeline stage.

Stage	Test Procedures	Research Metrics	Difference
Detection	Standard, visible markings only: temporary markings excluded and visibility above 1 km (ISO 17361:2007); daylight above 2000 lux, no precipitation, lanes 3.5 to 3.7 m (Euro NCAP); solid, dashed, and raised pavement markers (NHTSA)	F1 or accuracy on image benchmarks with night, rain, shadow, and crowded scenes (Sections 4 and 5)	Benchmarks test conditions the procedures exclude; raised pavement markers and worn markings are rare in benchmarks
Tracking	No separate requirement; warnings in repeated trials must fall within a 30 cm zone (ISO 17361:2007); one trial per condition (NHTSA)	Temporal F1, flickering and missing rates on VIL-100 and OpenLane-V (Section 6)	Temporal stability is measured per frame, not as consistency of the warning position
Warning	Warning between the earliest and the latest warning line, 0.3 m outside the boundary for cars, at departure rates up to 0.8 m/s, and no warning over 1000 m inside the lane (ISO 17361:2007); warning within 0.75 m of the line and before 0.3 m of departure, at 0.2 to 0.6 m/s and 72.4 km/h, all 50 trials passed (NHTSA)	Departure detection rate, per frame accuracy, false warning rate, and TLC (Section 7.1)	Few studies report the warning position relative to the line, the measure every procedure uses
Steering	Distance to lane edge after intervention at 72 km/h and 0.2 to 0.6 m/s (Euro NCAP); maximum offset 0.4 m for light vehicles (ISO 11270); no line crossing and lateral jerk limit (UN R79); no departure beyond 0.3 m and a secondary departure test (NHTSA)	RMS or maximum lateral error, mostly in simulation; driver workload and conflict in shared control (Section 8)	Few studies report distance to lane edge or jerk, and few test at the procedures' lateral velocities

Abbreviations: ISO, International Organization for Standardization; NCAP, New Car Assessment Programme; NHTSA, National Highway Traffic Safety Administration; RMS, root mean square; TLC, time to lane crossing; UN R79, UN Regulation No. 79.

Neither the NHTSA nor the Euro NCAP procedure addresses the mixed traffic and inconsistently marked roads that Section 4 identifies as underexplored, and neither references conditions specific to Southeast Asia.

8. Steering Intervention

Steering intervention is the final stage of the pipeline. It converts a tracked lane position and a warning decision into an automated steering correction and is present only in lane keeping assist systems. A warning only LDWS ends with the alert of Section 7, which may be a vibration of the steering wheel. Haptic shared control, in which the system applies a guiding steering torque that the driver can override, is included in this section because it acts on the steering.

Classical steering control treated lane keeping as a linear or formally verified control problem. Marino, Scalzi, and Netto [198] (2011) proposed a nested proportional integral

derivative structure that separates yaw rate control from lateral offset control as two coupled loops rather than a single combined objective. Enache et al. [199] (2010) developed a hybrid automata and composite Lyapunov function framework that formally guarantees stability across authority transitions between the driver and assist system. As with most formal control guarantees, however, the analysis assumes a perfect lane position estimate and does not address the perception side uncertainty that Sections 3 and 6 show persists in practice. A 2010 to 2012 series of hardware in the loop (HIL) validated studies by the present author and colleagues [200,201] developed a nested steering control design for lane keeping, double lane change, and sine steer manoeuvres on a rig coupled to CarSim, within the same nested outer loop and inner loop control tradition.

A second strand of classical and near-classical work treats authority sharing between driver and system as the central design problem rather than control accuracy alone. Merah et al. [202] applied a fuzzy sliding mode controller to shared lane-keeping control in an electric vehicle, and Liang, Yin, and Nie's [203] 2021 multi-objective model predictive control (MPC) formulation balances lane-keeping and obstacle-avoidance objectives and weights driver authority within the same optimisation. Nakade et al.'s [204] 2023 study extends shared control into human factors, which are largely absent from the purely control theoretic literature above. It proposes a multilevel haptic authority sharing scheme between driver and automated steering assist and reports improvements in driver acceptance and perceived smoothness rather than tracking error alone. A lane-keeping assist system that a driver distrusts and disables is, from a road safety standpoint, equivalent to one that was never fitted. The classical control formulations above are validated mainly against a tracking error or stability criterion, whereas the shared control literature treats sustained driver acceptance as a design objective on the same footing as control accuracy.

End-to-end learned steering prediction, by contrast, removes the separation between lane detection and control law and predicts a steering angle directly from image input. Ye et al. [205] adapted a YOLOv5 backbone for this purpose, and Saleem et al.'s RPRP-SAP [206] (2024) applied a residual block convolutional predictor benchmarked on comma2k19, the Udacity steering benchmark, and the CARLA simulator, three widely used evaluation sources that are still mainly drawn from simulators or benchmarks. Both show a trade-off common to end-to-end formulations elsewhere in this review: removing the explicit detection stage can improve accuracy on the training distribution but sacrifices the interpretability of a system whose failure mode can be traced to a specific stage.

Reinforcement learning is the most recent strand of the steering intervention literature reviewed here. Kim et al. [207] trained a deep deterministic policy gradient (DDPG) agent that observes surrounding vehicle and object information from LiDAR rather than from camera-based lane detection. This sensor-redundant design maintains lane position even when the camera-based pipeline that is the focus of this review is degraded. Cheng et al.'s [208] 2023 method combines a soft actor-critic policy with a predictive safety filter that guarantees safe lane-keeping motion even when the learned policy alone would violate a safety constraint. The safety filter addresses a central objection to reinforcement learning in a safety-critical control loop, the absence of a formal guarantee. Hosseini Miangoleh, Aghdasian, and Abdollahi's BLIP-FusePPO [209] (2025) fuses vision language model semantic embeddings, geometric LiDAR state, and PID feedback within a single proximal policy optimisation agent, with a hybrid reward covering semantic alignment, lane keeping, obstacle avoidance, and speed. The cost is the added runtime overhead that a vision language model introduces relative to classical control.

Model predictive control has continued to develop alongside the reinforcement learning strand above. Garcia Montoya et al.'s [210] 2023 comparative study evaluates multiple model predictive control schemes and quadratic programming (QP) solver configurations

for real-time feasibility on lane-keeping assist hardware, and Hong, Moon, and Hwang [196] address a less-studied failure mode, the lateral jerk and hysteresis discomfort that occurs when authority switches abruptly between operational modes, with a softly switched formulation that smooths the transition. That this topic remained active in 2025 suggests that smooth authority transition is not yet solved within the well-established model predictive control tradition.

The systematic search identified 163 steering intervention studies (Table 2), the largest group after detection. Most were evaluated without a vehicle on the road: 76 in numerical simulation alone, usually CarSim, TruckSim, CarMaker, or MATLAB and Simulink; 50 in a driving simulator with human drivers; 11 on a hardware-in-the-loop bench without a driver; and 6 offline on recorded driving data. Only 20 closed the control loop on a real vehicle (Table 13). The robust control strand quantifies the trade offs of the classical designs: an H_∞ design gives a larger stability radius than PID and linear quadratic Gaussian control at the same lateral tracking error [211], three linear parameter varying designs have been compared on a robotised Renault ZOE on a closed track [212], and a Takagi Sugeno fuzzy extension controller halves the peak lateral deviation of a PID controller on a hardware in the loop bench, 0.35 m against 0.68 m [213]. Heavy vehicles form a distinct subgroup with their own constraints, from keeping every unit of a multi-trailer combination inside the lane [214] to a Level 2 lane-keeping system on a Class 8 truck [215].

Shared control is the most frequent design theme in the steering literature found by the search, and most of it is tested with human drivers in a simulator. Haptic designs that adapt their authority to time to lane crossing keep the safety margin of a stiff controller with less conflict torque [216]. An MPC-based haptic system with an embedded driver model gave a lateral error of 0.29 to 0.33 m RMS, depending on the cost function setting, against 0.51 m for a commercial lane-keeping assist system in a study of 19 drivers [217]. Human-like intermittent steering that acts only when an inverse TLC threshold is crossed raises the time to lane crossing measure reported by the authors from 2.79 s to 4.91 s, at the cost of a larger lateral deviation [218]. Simulator studies also measure how drivers respond to imperfect assistance: a lateral offset error of 0.66 m in a lane-keeping system, of the kind a misaligned camera would cause, shifted the driver's mean lane position by 0.1 m [219]. On a test track, 15 truck drivers departed the lane less often with any of the three haptic designs when distracted, and rated continuous assistance as most usable [220]. Counter-steering against an unsafe lane change initiated by the driver, tested with 80 drivers, avoided every collision when the intervention was automatic [221].

Learned controllers are fewer but recent. An action-robust reinforcement learning agent keeps the lateral error at 0.23 m RMS on snowy CARLA routes, against 0.42 m for a standard DDPG agent [222]. An uncertainty-aware planner reduces the lateral deviation that an adversarial road patch induces in OpenPilot by 55 to 91 percent [223]. A recurrent network trained to imitate MPC has been verified for robustness and reachable sets [224], and an end-to-end network trained with labels corrected by TLC kept a full-scale vehicle within a mean lateral displacement of 0.092 m at 40 km/h on an ISO 11270 proving ground route [195]. Few studies model perception error inside the steering loop. Hober et al. [225] measured a Mobileye camera against real-time kinematic (RTK) ground truth on an Austrian test highway and found a mean marking detection error of 0.15 to 0.2 m, and Wang and Bian [226] treated lane loss under glare as an intermittent sensor fault, cutting the maximum lateral offset on a highway from 0.55 m to 0.1 m.

Table 13. Included steering intervention studies that closed the control loop on a real vehicle, with the lateral tracking result reported (as published).

Study	Year	Vehicle and Site	Controller	Reported Result
Abualhoul et al. [227]	2018	Two Mitsubishi i-MiEV, platoon tests, Madrid	Camera lane centring for a platoon	Mean lateral deviation below 0.2 m, against up to 1 m without
Kang et al. [228]	2018	Hyundai Tucson, Korea	Kinematic look-ahead control	Lateral offset within 0.2 m at 60 km/h; expert driver within 0.4 m
Raffone et al. [229]	2019	Fiat 500X and Jeep Renegade, Orbassano track	Look ahead LQ control	Below 0.2 m in a lane change; about 0.8 m entering the sharpest banked curve
Solmaz et al. [230]	2019	Ford Mondeo, Gratkorn test track	LKA with Kalman delay prediction	Stable up to 90 km/h, against oscillation above 70 km/h without (figures)
Zhao et al. [231]	2019	Low-speed electric vehicle	Fuzzy multimodel lateral control	Maximum error 0.12 m in simulation; field test reports steering tracking only
Reagan et al. [197]	2019	Four production cars, public highway, 80.5 km/h	Production lane departure prevention	Crossing kept under 35 cm in all drifts for the best system, in under 20% of drifts for two others
Tominaga et al. [232]	2019	Mitsubishi Outlander PHEV, highway	MPC on GNSS and map	RMS lateral error 0.19 m
Jin [233]	2019	Electric test vehicle, China	Fuzzy authority shared control	Maximum tracking error about 10 to 12 cm at 30 and 80 km/h
Jung et al. [195]	2020	Full scale vehicle, KIAPI proving ground	End to end network with TLC labels	Mean lateral displacement 0.092 m at 40 km/h
Xu et al. [234]	2020	Lincoln MKZ, Mcity	Preview LQR with barrier function	Below 0.14 m at Mcity with RTK lanes; peak about 0.40 m on open roads with the camera
Chen et al. [235]	2020	Test vehicle, 30 to 65 km/h, China	Takagi Sugeno fuzzy H_∞	Peak deviation 0.271 m in the vehicle test (0.290 m without compensation)
Tominaga et al. [236]	2020	Mitsubishi Outlander PHEV, snow-covered highway, Hokkaido	MPC with delay compensation	RMS lateral error below 0.6 m
Roozendaal et al. [220]	2020	Volvo truck, test track, 15 drivers	Three haptic designs	Fewer departures when distracted
Farah et al. [237]	2020	Tesla Model S, Dutch motorways, 19 drivers	Production Autosteer	Driver and maker views of the design domain differ in 68.7% of cases without markings, 81.2% at off ramps
Atoui et al. [212]	2021	Renault ZOE, Satory track	Three LPV designs	RMS lateral error 0.10 to 0.15 m across designs
Cheng et al. [238]	2021	Bus, test site, below 20 km/h	Lane keeping with obstacle avoidance	Maximum error about 0.4 m
Wang and Bian [226]	2023	Test vehicle, Xiangyang highway	Fault tolerant control for lane loss	Maximum offset 0.1 m, against 0.55 m without
Ward et al. [215]	2023	Class 8 truck, NCAT track	Nonlinear MPC on a GNSS path	Mean lateral error 1.47 cm, standard deviation 27.28 cm
Surblys et al. [239]	2025	Three production cars, Lithuania	Production lane keeping	Strongly skewed lateral acceleration on worn markings (skewness up to 3.10)
Sarabia et al. [240]	2026	Renault Twizy, closed track, 10 drivers	Shared nonlinear MPC	RMS path error 0.28 m at the highest authority setting (0.69 m at the lowest)

Abbreviations: GNSS, global navigation satellite system; KIAPI, Korea Intelligent Automotive Parts Promotion Institute; LKA, lane keeping assist; LPV, linear parameter varying; LQ, linear quadratic; LQR, linear quadratic regulator; MPC, model predictive control; NCAT, National Center for Asphalt Technology; RMS, root mean square; RTK, real time kinematic; TLC, time to lane crossing.

Some of the strongest evidence in this section comes from an empirical study of deployed systems. Wang et al.'s OpenLKA [241] (2025) is described by its authors as the

first open dataset of lane keeping assist behaviour recorded from mainstream production vehicles rather than from a research prototype in simulation. Using that dataset, Wang et al. [242] report what they describe as the first comprehensive empirical analysis of real-world lane-keeping assist performance. They categorise observed failures into perception, planning, and control errors, and report a behaviour that had not been documented before: production systems tend to follow a fixed lane centring strategy that produces outward drift that increases linearly with road curvature, whereas human drivers proactively steer slightly inward on the same curved segments. The finding is in tension with the curvature aware model predictive control and reinforcement learning formulations reviewed earlier, none of which reports this curvature drift behaviour. It is strong evidence that a gap remains between what the steering intervention literature optimises for in simulation and how deployed systems behave on real roads (Table 14).

Further studies of production vehicles support the OpenLKA finding. In induced drifts on a public divided highway, four production lane departure prevention systems differed widely: the best kept every drift towards a solid marking from crossing it by more than 35 cm, while two did so in fewer than 20 percent of drifts, and owners activated the better systems more often [197]. On two routes of about 600 km in North Holland, a production lane-keeping system and a lane departure warning system detected both lane lines least often at night in rain with street lighting [243]. In a field test of Tesla Autosteer with 19 drivers on Dutch motorways, the drivers' view of where the system could operate differed from the manufacturer's in 68.7 percent of cases with no lane marking and 81.2 percent at off ramps [237]. Three production lane-keeping systems tested on worn and broken markings in Lithuania produced markedly skewed lateral acceleration on the poorest sections [239]. Together, they point to marking quality and visibility as limits on deployed lane keeping, the conditions that Section 9.2 examines for Southeast Asian roads.

Table 14. Steering intervention control paradigms reviewed in Section 8, from classical control to empirical deployment evidence.

Paradigm	Representative Methods	Key Idea
Classical nested loop or PID	Marino, Scalzi, and Netto [198] (2011); Em et al. [200] (2010); Jamaluddin et al. [201] (2012)	Separate yaw rate and lateral offset control loops
Hybrid automata, formal control	Enache et al. [199] (2010)	Formal stability guarantee across transfers of authority between driver and assist system
Shared control (fuzzy, haptic, MPC)	Merah et al. [202] (2016); multilevel haptic control [204] (2023); Liang, Yin, and Nie [203] (2021)	Authority shared between driver and automated system
End to end learned steering	Ye et al. [205] (2021); Saleem et al. [206] (2024)	Steering angle predicted directly from the image
Reinforcement learning	Kim et al. [207] (2023); RL with a safety filter [208] (2023); BLIP-FusePPO [209] (2025)	Learned policy, in some cases with a formal safety filter guarantee
Model predictive control	Comparative MPC and QP study [210] (2023); Hong, Moon, and Hwang [196] (2025)	Constrained optimisation in real time; smooth switching between authority modes
Empirical deployment evidence	OpenLKA [241] (2025); Wang et al. [242] (2025)	Behaviour of production LKA systems in real traffic

Abbreviations: LKA, lane keeping assist; MPC, model predictive control; PID, proportional integral derivative; QP, quadratic programming; RL, reinforcement learning.

Each stage reviewed in Sections 6–8 shows continued refinement, with learned temporal tracking, driver behaviour-aware warning logic, and reinforcement learning based

control among the most recent developments. However, the deployment evidence above suggests that the literature on any single stage does not fully predict how the assembled pipeline behaves in a production vehicle, a gap to which Section 9 returns.

9. Future Directions

The preceding sections reviewed each stage of the LDWS pipeline largely on its own terms. Read together, they show three gaps that recur across several stages. Sections 9.1–9.3 discuss each as a direction for future research. Section 9.4 then outlines four emerging directions that do not yet form an established body of work.

9.1. Evaluation Standardisation Beyond Detection

Two-dimensional detection has converged on CULane and TuSimple and is approaching saturation (Section 5.1); no other stage of the pipeline has. Three-dimensional detection on OpenLane has not settled on a single primary metric (Section 5.2). Lane tracking has two public video benchmarks, VIL-100 since 2021 and OpenLane-V since 2023, on which only a minority of tracking studies report results (Section 6). Steering intervention is still evaluated mostly in simulation: 20 of the 163 included studies close the loop on a real vehicle, and OpenLKA is the only large open dataset of production behaviour identified in this review (Section 8). The most immediate opportunity is in tracking, where wider adoption of the video benchmarks and their temporal metrics would extend the comparison of Table 7 to the many tracking studies that still report results only on their own sequences.

9.2. Mixed Traffic and Southeast Asian Driving Conditions

The datasets underlying nearly all of the methods reviewed in Sections 3 and 6–8 were collected in North America, Europe, or East Asia, under consistent lane marking and largely homogeneous traffic. The systematic search confirms the imbalance: of the 695 included studies, 12 report evaluation data collected at least partly in Southeast Asia. Ten use the authors' own recordings from Malaysia [162,185,244–246], Singapore [247,248], and Indonesia [249–251]. These range from about 60 sampled images to about 70,000 frames, but most contain a few hundred to a few thousand. The other two use data that only partly cover the region: OpenLane-V2 Subset-B, whose nuScenes data come from Boston and Singapore [252], and a test fleet driven in ten countries, including Malaysia [170]. Using Malaysia as the case with the most available evidence, this section covers four topics: traffic composition, lane marking condition, the performance of existing methods on local roads, and the data that would be needed to close the gap. Table 15 summarises the evidence.

Traffic composition.

Motorcycles made up 46.2 percent of Malaysia's 32.5 million registered vehicles in 2021 [253], and powered two- and three-wheelers accounted for 63 percent of the 4539 road deaths reported for the same year [254]. The pattern is regional: powered two- and three-wheelers make up about 52, 83, and 93 percent of the registered fleets of Thailand, Indonesia, and Viet Nam, respectively [1]. Motorcycles share lanes with cars and heavy vehicles and keep lateral clearances that depend on vehicle type [255], so a lane boundary is often partly occluded by a vehicle travelling within the same lane. Analysis of police crash data from 2012 to 2022 identifies motorcycles as the road user most involved in Malaysian crashes [256]. None of the benchmarks in Section 4 label motorcycles sharing a lane with the ego vehicle.

Lane marking condition.

Field trials on Malaysian federal roads found that marking retroreflectivity fell steeply within about two months of laying. At the most heavily trafficked site, thermoplastic markings retained 101 mcd/m^2/lx dry and 30.6 wet after the equivalent of four years, against the specification's initial minimum of 300 dry and 75 wet [257]. The same study notes that the national road works specification sets only this initial minimum, with no in-service requirement [257]. Night drivers surveyed in Malaysia rated conventional markings as usually faded or worn [258]. Missing road markings raised the probability of single vehicle fatal motorcycle crashes in Malaysian police data [259], and rainfall raised-single vehicle crashes on rural highways, while delineation reduced them [260]. The link to machine vision has been measured elsewhere: camera detection quality rises with retroreflectivity [261], and at night in heavy rain, recognition of white lines fell to 70 and 50 percent at retroreflectivity of 142 and 104 mcd/m^2/lx, respectively [189]. This review found no study that measures LDWS performance against marking retroreflectivity on Southeast Asian roads, so this link is inferred rather than shown for the region.

Table 15. Evidence on Malaysian and Southeast Asian conditions relevant to LDWS, discussed in Section 9.2.

Aspect	Evidence	Source
Traffic composition	Motorcycles 46.2% of registered vehicles, Malaysia, 2021	[253]
	Powered two- and three-wheelers 63% of 4539 reported road deaths, Malaysia, 2021	[254]
	Powered two- and three-wheelers about 52%, 83%, and 93% of registered fleets, Thailand, Indonesia, Viet Nam	[1]
	Vehicle type dependent lateral clearance in mixed traffic, Malaysian urban merge	[255]
Marking condition	Steep early loss of retroreflectivity on federal roads; initial minimum only, no in service requirement	[257]
	Night drivers rate conventional markings as usually faded or worn	[258]
Crash risk	Missing markings associated with single vehicle fatal motorcycle crashes	[259]
	Rainfall raises, delineation lowers, single-vehicle-crashes on rural highways	[260]
Method performance	Lane detection 94.06% (day), 95.36% (night); departure detection 81.18%; worn markings and glare cause false positives (Melaka)	[162]
	Fading markings and shadows cause false warnings (Malaysian dataset)	[245]
	Networks trained on TuSimple score lowest on rain frames from Malaysian roads; F1 about 67% at 96% accuracy	[244]
Public data	Melaka day and night clips with automated lane boundary annotations; one city, no rain	[112,113]

Abbreviations: LDWS, lane departure warning system.

Performance of existing methods on local roads.

The few evaluations on Malaysian footage point the same way. On 27 clips of urban roads and highways in Melaka, a classical vision-based framework detected 94.06 percent of lane markings by day and 95.36 percent at night, but only 81.18 percent of lane departures. Worn markings, wet surfaces, glare, and painted arrows were the main sources of false positives [162]. Teo et al. [245] also attribute false warnings on a Malaysian dataset to fading markings and shadows. When three segmentation networks trained on TuSimple were tested on frames from Malaysian roads, all three scored lowest on the rain category, and F1 was about 67 percent even though accuracy was about 96 percent [244]. The authors attribute the drop to dark, missing-lane, and rainy frames, which are absent from TuSimple. Yaamini et al. [262] report a similar loss of accuracy under mixed traffic and inconsistent

marking on Indian roads. These are small studies, two of them by the present author and colleagues, and they do not share a common protocol. Even so, they consistently suggest that accuracy reported on the benchmarks of Section 4 does not transfer unchanged to Southeast Asian roads.

Data needed.

Public lane data from Malaysia are beginning to appear. The present author has released the Melaka footage used in [162]: 27 clips and about 70,000 frames by day and at night, with a clip-level annotation table and automated lane boundary annotations generated with YOLOP [112,113]. This release comes from one city, one vehicle, and one low-resolution camera and contains no footage in active rain. Its geometric labels are machine-generated rather than verified. To evaluate the methods reviewed here under Southeast Asian conditions, a benchmark would need, at minimum: footage from several cities and road classes, including rural roads with missing or worn markings; monsoon rain by day and at night; verified geometric lane boundaries per frame, with marking condition and occluding motorcycles labelled; and synchronised vehicle signals, so that tracking stability, warning lead time, and false alarm rate can be measured against time to lane crossing as well as detection F1. Existing Malaysian data could seed such a benchmark, but none yet meets these requirements.

9.3. Bridging Simulation Based Design and Deployed Behaviour

The OpenLKA finding of outward curve drift in production systems (Section 8) does not show that the simulation-based literature is wrong on its own terms. It does suggest that validation in simulation alone, which most of the methods reviewed in Section 8 rely on, does not by itself predict deployed behaviour. Future work could validate proposed methods against real-world deployment data of the kind OpenLKA has begun to make available. Doing so would help narrow the clear gap identified in this review between the algorithmic literature and production reality.

9.4. Emerging Directions

Topology reasoning.

Topology reasoning asks whether a detected lane connects to, forks from, or merges with another lane or traffic element. OpenLane-V2 introduced this task and TopoMLP advanced it, but it remains largely unaddressed in the LDWS literature, although it is relevant to lane change and lane merge warning beyond simple departure detection.

Vision language supervisory systems.

Supervisory systems based on vision-language models and other large models, such as LKAlert (Section 7.1), are a warning approach that explains and supervises a black-box production system. Such systems are likely to become more relevant as more vehicles ship with proprietary lane-keeping assist systems that cannot be reviewed.

Embedded and edge deployment cost.

The embedded results reviewed in Sections 3.2, 6 and 7.1 range from multitask detection on a Jetson TX2 to tracking on ARM processors and warning on a Jetson Orin Nano. They suggest that computational cost is becoming a design objective alongside accuracy, for deployment in cost-sensitive markets as well as in flagship vehicles with dedicated accelerator hardware.

Interpretability and certifiability.

Interpretability and certifiability remain largely unaddressed for the learned detection and control methods this review covers. The ISO 17361 standard and the current NHTSA and Euro NCAP protocols reviewed in Section 7.2 specify what a system's output must achieve under test, not how a deep learning model arrived at that output. None of the methods reviewed in Section 3 or Section 8 reports the kind of evidence a functional safety case typically requires: that a specific failure can be traced to a specific, correctable cause within the model rather than treated as an opaque statistical error rate. A fuller explanation of why production lane-keeping assist systems drift outward on curved roads (Section 8) would plausibly require this kind of interpretability (Table 16).

Table 16. Summary of the three gaps across stages (Sections 9.1–9.3) and the four emerging directions (Section 9.4) identified in this review.

Gap	Where Identified	Suggested Direction
Gaps across stages		
Evaluation fragmented beyond 2D detection	Sections 5.2, 6 and 8	Wider adoption of the video lane benchmarks and their temporal metrics; a standard 3D and topology metric
No Southeast Asian mixed traffic benchmark	Sections 4 and 9.2	Extend existing Malaysian data into a benchmark with verified lane geometry, rain, motorcycles, and metrics for each stage
Gap between simulation and deployment	Sections 8 and 9.3	Validate proposed methods against data from deployed systems such as OpenLKA [241]
Emerging directions		
Topology reasoning little used in LDWS	Sections 3.3 and 9.4	Apply topology reasoning of the OpenLane-V2 [93] and TopoMLP [101] kind to lane change and merge warning
Supervision based on vision language models	Sections 7.1 and 9.4	Extend explainable supervision of the LKAlert [190] kind to more production LKA systems
Embedded and edge deployment cost	Sections 3.2 and 9.4	Design for computational cost as well as accuracy, for cost-sensitive markets
Interpretability and certifiability	Sections 7.2, 8 and 9.4	Explanations for learned detection and control that trace failures and support certification

Abbreviations: 2D, two dimensional; 3D, three dimensional; LDWS, lane departure warning system; LKA, lane keeping assist.

10. Conclusions

This review has examined the four stages of a lane departure warning system (lane detection, lane tracking, warning decision logic, and steering intervention) together with the regulatory tests that now apply to them. Two-dimensional lane detection has converged on CULane and TuSimple and reports high accuracy on both, while three-dimensional detection has not yet settled on a common metric. The later stages have a smaller and less standardised body of evaluation: lane tracking has two public video benchmarks that only a minority of studies use, warning methods report different metrics, and steering intervention is validated mostly in simulation. Evidence from deployed lane-keeping assist systems shows that production behaviour can differ from what designs validated in simulation predict. The NHTSA confirmation test procedure of November 2024 and the Euro NCAP Lane Support Systems protocol now give a shared basis for assessing production systems, although neither addresses mixed traffic or degraded markings. Two limitations apply to these conclusions. First, the performance figures are taken from each

paper's own results rather than from a common reevaluation, so they show trends rather than a controlled ranking. Second, the literature reviewed, like the benchmarks it relies on, comes mainly from North America, Europe, and East Asia. The main needs that follow from this review are common evaluation for the stages after detection and evaluation under the road conditions of underrepresented regions.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/vehicles8110291/s1, Table S1: Studies included in the review, with the data extracted from each study; PRISMA 2020 checklist. References [263–818] are cited in the Supplementary Materials.

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Institutional Review Board Statement: Not applicable. This is a literature review and did not involve human participants, animals, or plants.

Informed Consent Statement: Not applicable. This is a literature review and did not involve human participants or their data.

Data Availability Statement: The search strings are given in Appendix A, and the list of included studies with the data extracted from each is provided as Supplementary Table S1. No other new data were created in this study.

Conflicts of Interest: The author declares no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

ADAS	Advanced Driver Assistance System
BEV	Bird's Eye View
BiLSTM	Bidirectional Long Short Term Memory
CNN	Convolutional Neural Network
ELM	Extreme Learning Machine
fps	Frames Per Second
GB/T	Recommended National Standards (China)
HD	High Definition
HIL	Hardware in the Loop
IPM	Inverse Perspective Mapping
ISO	International Organization for Standardization
LDW	Lane Departure Warning
LDWS	Lane Departure Warning System
LiDAR	Light Detection and Ranging
LKA	Lane Keeping Assist
LSS	Lane Support Systems
LSTM	Long Short Term Memory
MPC	Model Predictive Control
NCAP	New Car Assessment Programme
NHTSA	National Highway Traffic Safety Administration
OLS	OpenLane-V2 Score
PID	Proportional Integral Derivative
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
QP	Quadratic Programming
RESA	Recurrent Feature Shift Aggregator
RL	Reinforcement Learning

RVLD	Recursive Video Lane Detection
SCNN	Spatial Convolutional Neural Network
TLC	Time to Lane Crossing
UFLD	Ultra Fast Structure Aware Deep Lane Detection
UN	United Nations
VLM	Vision Language Model
WHO	World Health Organization
YOLO	You Only Look Once

Appendix A. Search Strings

Table A1. Search strings and records returned, by block and database (OpenAlex searched 15 October 2026; IEEE Xplore searched 16 October 2026).

Block	Database	Search String or Filter	Records
D (lane detection)	OpenAlex	`title_and_abstract.search:("lane detection" OR "lane marking detection" OR "lane line detection" OR "lane boundary detection" OR "3D lane detection" OR "lane marker detection") AND (TuSimple OR CULane OR CurveLanes OR LLAMAS OR BDD100K OR OpenLane OR "ONCE-3DLanes" OR "Apollo Synthetic" OR "VIL-100" OR "Caltech Lanes"), publication_year:2018-2026, type:article| conference-paper`	566
	IEEE Xplore	`("All Metadata":"lane detection" OR "All Metadata":"lane marking detection" OR "All Metadata":"lane line detection" OR "All Metadata":"lane boundary detection" OR "All Metadata":"3D lane detection" OR "All Metadata":"lane marker detection") AND ("All Metadata":TuSimple OR "All Metadata":CULane OR "All Metadata":CurveLanes OR "All Metadata":LLAMAS OR "All Metadata":BDD100K OR "All Metadata":OpenLane OR "All Metadata":"ONCE-3DLanes" OR "All Metadata":"Apollo Synthetic" OR "All Metadata":"VIL-100" OR "All Metadata":"Caltech Lanes")` Filters: Year 2018 to 2026; Content Type: Conferences, Journals, Early Access Articles	261
T (lane tracking)	OpenAlex	`title_and_abstract.search:"lane tracking" OR "video lane detection" OR "temporal lane detection" OR "lane detection in video" OR ("lane detection" AND ("Kalman filter" OR "particle filter" OR "temporal fusion" OR "multi-frame" OR "sequential")), publication_year:2018-2026, type:article| conference-paper`	319
	IEEE Xplore	`"All Metadata":"lane tracking" OR "All Metadata":"video lane detection" OR "All Metadata":"temporal lane detection" OR "All Metadata":"lane detection in video" OR ("All Metadata":"lane detection" AND ("All Metadata":"Kalman filter" OR "All Metadata":"particle filter" OR "All Metadata":"temporal fusion" OR "All Metadata":"multi-frame" OR "All Metadata":sequential))` Filters: Year 2018 to 2026; Content Type: Conferences, Journals, Early Access Articles	212
W (warning decision logic)	OpenAlex	`title_and_abstract.search:"lane departure warning" OR "lane departure detection" OR "lane departure prediction" OR "time to lane crossing" OR "time-to-lane-crossing" OR "time to line crossing", publication_year:2018-2026, type:article| conference-paper`	458
	IEEE Xplore	`"All Metadata":"lane departure warning" OR "All Metadata":"lane departure detection" OR "All Metadata":"lane departure prediction" OR "All Metadata":"time to lane crossing" OR "All Metadata":"time-to-lane-crossing" OR "All Metadata":"time to line crossing"` Filters: Year 2018 to 2026; Content Type: Conferences, Journals, Early Access Articles	163

Table A1. *Cont.*

Block	Database	Search String or Filter	Records
S (steering intervention)	OpenAlex	`title.search:"lane keeping assist" OR "lane keeping assistance" OR "lane keeping system" OR "lane keeping control" OR "lane departure prevention" OR "lane departure avoidance" OR "lane departure assist" OR "lane centering" OR "lane centring", publication_year:2018-2026, type:article| conference-paper` UNION `title_and_abstract.search:"shared control" AND "lane keeping", publication_year:2018-2026, type:article| conference-paper`	318
	IEEE Xplore	`"Document Title":"lane keeping assist" OR "Document Title":"lane keeping assistance" OR "Document Title":"lane keeping system" OR "Document Title":"lane keeping control" OR "Document Title":"lane departure prevention" OR "Document Title":"lane departure avoidance" OR "Document Title":"lane departure assist" OR "Document Title":"lane centering" OR "Document Title":"lane centring" OR ("All Metadata":"shared control" AND "All Metadata":"lane keeping")` Filters: Year 2018 to 2026; Content Type: Conferences, Journals, Early Access Articles	144
R (earlier reviews)	OpenAlex	`title.search:lane AND (detection OR departure OR keeping OR tracking OR marking) AND (review OR survey OR "state of the art" OR overview), type:article| conference-paper| review`	99
	IEEE Xplore	`"Document Title":lane AND ("Document Title":detection OR "Document Title":departure OR "Document Title":keeping OR "Document Title":tracking OR "Document Title":marking) AND ("Document Title":review OR "Document Title":survey OR "Document Title":"state of the art" OR "Document Title":overview)` Filters: No year limit; Content Type: Conferences, Journals, Early Access Articles	28

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