Multi-Sensor Fusion in Autonomous Vehicles: A Technical-Thematic Analysis

J.M.L.B. Jayasundara, M.S. Shafana, and R.M. Nayanajith Rathnayaka

Abstract This paper presents a comprehensive technical-thematic review of multi-sensor fusion techniques employed in autonomous vehicles (AVs), focusing on the system-level attributes that govern real-world applicability. By analysing 40 recent studies, we classify and compare fusion approaches such as early, middle, tiered, and adaptive fusion in terms of their applications (e.g., localization, object detection, vehicle tracking), sensor combinations, performance outcomes, and implementation challenges. A detailed thematic matrix highlights how different fusion architectures are tailored to specific AV use-cases, such as urban navigation, GPS-denied positioning, and fault detection. Additionally, this review integrates visual analytics including application-to-fusion mapping, challenge frequency analysis, dataset usage trends, and real-time capability distribution. The findings indicate that while multi-level and adaptive fusion strategies show increasing applicability, real-time deployment remains constrained by high computational demands and synchronization issues. This study identifies common limitations across current implementations. Finally, this study suggests future directions for developing scalable, resilient, and efficient sensor fusion systems tailored for safety-critical autonomous driving environments.

***Index Terms*— Autonomous Vehicles, Fusion Architectures, Localization and Object Detection, Real-Time Systems, Sensor Fusion**

I. Introduction

AUTONOMOUS vehicles (AVs) rely on the fusion of data from multiple sensors such as LiDAR, radar, cameras, GNSS, IMUs, and ultrasonic sensors to build an accurate and context-aware understanding of their environment. While the technical design of sensor fusion algorithms has been extensively explored, there is a growing need to assess their thematic and application-level behavior in real-world deployments. This review paper aims to conduct a technical-thematic evaluation of multi-sensor fusion methods with a specific focus on use-cases, sensor setups, performance outcomes, and implementation challenges. Rather than merely categorizing fusion methods by type (early, middle, late), this study examines how these methods are applied in practice such as in urban navigation, multi-object tracking, GPS-denied environments, and adaptive cruise control systems. By synthesizing system-level attributes from 40 peer-reviewed studies and presenting insight-driven visual analyses, this paper aims to offer a structured understanding of how sensor fusion techniques are currently applied and where the research and development gaps remain. This work provides critical guidance for developers, researchers, and system integrators working toward scalable, safe, and context-resilient autonomous navigation systems.

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II. Literature Review

This review adopts a structured approach to explore the technical foundations of sensor fusion in autonomous vehicles (AVs), focusing on how fusion architectures, levels, sensor combinations, and modelling techniques have evolved. A systematic selection and evaluation of relevant literature was carried out, targeting peer-reviewed journal articles, conference proceedings, and technical reports published between 2018 and 2024. Databases such as IEEE Xplore, ScienceDirect, SpringerLink, and Google Scholar were used to identify studies containing experimental or simulation-based implementations of sensor fusion for AV-related tasks. A total of 40 studies were selected based on inclusion criteria such as relevance to AV systems, clear fusion framework descriptions, sensor modalities used, and performance metrics reported.

Table 1 provides a structured summary of the reviewed literature, categorizing each study by its fusion architecture, sensors employed, application domain, key challenges, dataset characteristics, and performance outcomes. It should be noted that the field employs varied terminology for fusion strategies terms, such as "middle fusion", "feature-level fusion", "late fusion", etc. Additionally, some studies implement hybrid or specialized approaches such as "tiered fusion," which involves multiple sequential fusion stages, or "adaptive fusion," which dynamically adjusts fusion strategies based on runtime conditions. Performance metrics are categorized qualitatively as "High," "Medium," or "Low" due to the heterogeneity of evaluation methods, datasets, and reporting standards across the reviewed studies, enabling standardized cross-study comparison despite diverse quantitative benchmarks.

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III. METHODOLOGY

This review follows a thematic review approach to analyze recent advancements in multi-sensor fusion techniques for autonomous vehicles (AVs). This review was conducted by selectively analyzing recent research articles related to multi-sensor fusion techniques in autonomous vehicles (AVs). Relevant studies were handpicked primarily through targeted searches on Google Scholar using keywords such as "autonomous vehicles," "sensor fusion," "object detection," and "real-time systems." The selection focused on works published between 2018 and 2025 that provided insight into fusion architectures, sensor combinations, application areas, and performance challenges. A total of 40 papers were reviewed, emphasizing those with practical relevance to AV systems.

The selected studies were categorized based on a predefined thematic analysis framework consisting of the following dimensions: (1) Fusion Architecture, (2) Sensor Modalities, (3) Application Domain, (4) Fusion Objective, (5) Operational Domain, (6) Performance Outcomes, and (7) Implementation Constraints. This structured framework enabled systematic identification of current trends, comparative assessment of fusion strategies, and recognition of research gaps in real-world deployment of sensor fusion techniques.

IV. RESULTS AND DISCUSSION

A. Fusion Type vs Application Mapping

The chart shows Fig. 1 that Sensor Fusion, Radar-Camera Fusion, and LiDAR-Camera Fusion are the most frequently used approaches across various applications. These fusion types are particularly dominant in tasks like object detection, urban navigation, and scene understanding. In contrast, more specialized methods like Adaptive Fuzzy-PSO Fusion or Semantic-Geometric Fusion appear less frequently but are linked to advanced tasks such as explainable localization and real-time trajectory estimation. The lower frequency of these specialized methods can be attributed to their higher implementation complexity and niche applicability, requiring domain-specific tuning that may not generalize well across diverse AV scenarios. Additionally, the computational overhead and lack of standardized frameworks for these advanced techniques further restrict their widespread deployment in production-level autonomous systems. This reflects both the popularity of certain sensor pairs and the adaptability of fusion strategies to specific use-case demands.

B. Sensor Combination Frequency

The analysis Fig. 2 reveals that Camera + LiDAR is the most common sensor combination, heavily favored for its balance between semantic and geometric data, making it ideal for tasks like object detection and 3D mapping. Radar + Camera and LiDAR + Radar also appears frequently, particularly in systems requiring robustness under low-light or adverse weather conditions. Less frequent but notable combinations such as Radar + Thermal + Camera suggest targeted applications like night-time detection. Overall, sensor pair selection reflects a trade-off between environmental coverage, accuracy, and cost, tailored to the specific operational demands of autonomous systems.

C. Performance Trend vs Dataset Type

The bar chart Fig. 3 illustrates a clear pattern: studies relying on simulated datasets tend to report high performance outcomes more frequently than those using real-world or hybrid datasets. This highlights the Simulation-to-Reality Gap, a critical challenge where controlled simulation environments yield near-optimal results that fail to translate to unpredictable real-world conditions due to the absence of sensor noise, weather variability, occlusions, and dynamic actor behavior. On the other hand, real and mixed datasets, while showing high performance in several cases, also exhibit more medium-level outcomes, likely reflecting the complexity and variability of real-world driving scenarios. This Simulation-to-Reality Gap has significant implications for the reliability of reported results in the field, as fusion systems validated primarily on simulated data may overestimate actual deployment performance and underrepresent failure modes encountered in safety-critical autonomous driving contexts. This discrepancy underlines the need for benchmarking fusion systems on diverse, real-life datasets to ensure practical viability and reduce overfitting to idealized environments.

D. Challenge Categorization and Frequency

The chart Fig. 4 highlights that real-time implementation and high computational cost are the two most frequently cited challenges across the reviewed studies, affecting 20 and 17 papers respectively. These reflect the core limitations in deploying multi-sensor fusion systems in real-world AVs, especially under constrained resources. Sensor misalignment and calibration sensitivity also appear repeatedly, underscoring the difficulty in maintaining consistency across diverse sensor platforms. Less frequently, issues such as infrastructure dependency, scalability, and GPS scarcity are noted, often specific to edge cases like V2X systems or urban tunnels. This distribution emphasizes a pressing need for optimized, adaptive fusion models tailored for practical, real-time deployment.

E. Fusion Type vs Performance Distribution

The stacked bar chart Fig. 5 illustrates how multi-level and deep fusion techniques dominate the high-performance category, reflecting their ability to combine semantic and geometric features effectively across sensor hierarchies. Adaptive fusion and cooperative fusion also yield strong results, particularly in GPS-deprived or dynamic environments. In contrast, early fusion methods, while still delivering high results in a few cases, show greater variability. Transformer-based and probabilistic methods, although promising, appear in fewer studies and show mixed performance, indicating a need for more robust deployment and benchmarking. The mixed performance of transformer-based methods can be attributed to their substantial data requirements and computational demands, which may not be fully accommodated by current AV hardware constraints, thereby limiting their effectiveness in real-time, resource-constrained deployment scenarios. Overall, the distribution favors advanced fusion architectures when accuracy and robustness are critical.

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F. Fusion Type vs Performance Distribution

The chart Fig. 6 reveals a clear trajectory in the evolution of sensor fusion strategies over the past five years. Multi-level and deep fusion techniques have shown consistent growth since 2020, highlighting their reliability and widespread adoption for robust perception. Adaptive fusion strategies, initially limited, have gained significant traction by 2024, indicating a shift towards context-aware and energy-efficient systems. Transformer-based fusion, while newer, shows rapid adoption, reflecting growing interest in attention mechanisms for autonomous decision-making. In contrast, probabilistic fusion remains stable but niche, typically used in scenarios demanding interpretability. This progression emphasizes the field's move from static models to more flexible, learning-driven frameworks.

G. Dataset use and Bias Analysis

The dataset usage analysis Fig. 7 highlights a prominent reliance on real-world datasets, comprising half of the reviewed studies, reflecting a positive trend toward practical validations. However, a substantial number of studies still use simulated environments, which, while beneficial for controlled testing, may introduce performance overestimation. The "Sim+Real" and "Other" categories indicate hybrid and customized datasets that aim to balance experimental control with realism. The low representation of lab-based and review studies suggests a gap in exploratory testing and meta-analysis. Overall, the pattern underscores a growing, yet uneven, shift toward deploying and benchmarking fusion systems in realistic conditions.

H. Real-time Feasibility Evaluation

The evaluation of real-time feasibility among the reviewed studies Fig. 8 reveals a nearly even split, with only 45% of sensor fusion systems being real-time capable. This stark limitation directly correlates with the findings from Figure 4, where high computational cost was identified as the second most frequent challenge (affecting 17 papers), alongside real-time implementation difficulties (affecting 20 papers), together representing the primary barrier to practical deployment of multi-sensor fusion in autonomous vehicles. Despite the high performance reported in many cases, computational demands and synchronization issues remain key obstacles to real-world deployment. The latency requirements for real-time operation vary significantly across applications: object detection typically requires processing times under 100ms to enable timely collision avoidance, while localization systems need updates at 10-50Hz, and path planning modules can tolerate slightly higher latencies (100-200ms) but demand consistent throughput for trajectory optimization. This indicates a pressing need for optimized architectures and lightweight algorithms to ensure practical utility in dynamic environments like urban streets. Many high-performing models fall short when tested under real-time constraints, highlighting a crucial research gap between theoretical success and operational feasibility.

I. Real-time Feasibility Evaluation

The heatmap Fig. 9 reveals clear patterns linking specific applications of sensor fusion to recurring technical challenges. Notably, urban navigation and object tracking show strong associations with computational cost, sensor misalignment, and real-time implementation issues. This suggests that high-density, dynamic environments intensify processing demands and synchronization complexity. ADAS and fault detection systems commonly face calibration sensitivity and lack of adaptability, reflecting the precision needed for safety-critical tasks. Meanwhile, use cases like low-light object recognition and GPS-denied localization are frequently challenged by environmental sensitivity and hardware limitations. Overall, the heatmap highlights that while sensor fusion applications are diverse, systemic challenges remain concentrated in areas requiring real-time robustness, accuracy, and environmental generalization.

V. CONCLUSION

This technical-thematic review analyzed 40 recent studies on multi-sensor fusion in autonomous vehicles, providing both categorical insights and statistical interpretations. From the Fusion Type vs Application Mapping, it is evident that object detection and urban navigation are the dominant focus areas, with fusion strategies such as LiDAR-Camera and Radar-Camera combinations prevailing in practical deployments. The Sensor Combinations Frequency analysis further confirms that Camera + LiDAR and Radar + Camera are the most frequently employed sensor pairs, reinforcing their effectiveness in complex environments. The Performance Trend vs Dataset Type visualization suggests a potential bias toward simulated environments, which often report higher success rates compared to real-world datasets. This indicates a gap in real-world robustness and calls for more field-tested solutions. The Challenge Categorization and Frequency diagram highlighted that real-time processing, sensor calibration, and environmental adaptability are the most common technical bottlenecks across studies. A cross-analysis of Fusion Type vs Performance demonstrated that adaptive and hybrid fusion strategies tend to yield higher accuracy, though they often come with increased computational demand. The Temporal Evolution of fusion techniques shows a clear rise in deep learning and transformer-based fusion methods in recent years, signaling a shift towards intelligent, data-driven architectures. From the Dataset Use and Bias Analysis, it became apparent that while real-world datasets are increasingly used, simulated and hybrid datasets still dominate experimental validations. In the Real-time Feasibility Evaluation, it was found that only a subset of high-performing models was also real-time deployable, stressing the need for lightweight optimization. The Use Case vs Challenge Heatmap underscored that urban navigation, while extensively studied, faces concentrated issues such as sensor synchronization and terrain variability.

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TABLE I
SUMMARY OF LITERATURE REVIEW

No	Article	Fusion Type	Sensors Used	Application	Key Challenges	Dataset Used	Performance
[1]	Huang et al., 2020	Early Fusion	Camera + Depth	Concurrent Scene Understanding	Simulation-only validation	CoRL2017	100% navigation success (simulated)
	Nabati and Qi, 2020	Middle Fusion	Radar + Camera	Object Detection, Range Estimation	Sensor noise, bad weather	nuScenes	High detection accuracy
[2]	Qingqing et al., 2021	Sensor Integration	LiDAR + GNSS + IMU + Wheel Encoder	Urban Navigation	Complex integration, not real-time	Custom/Urban Delivery	Accurate mapping and localization
[4]	Bae et al., 2021	Sensor Fusion	LiDAR + Camera	Closest In-Path Vehicle Detection (CIPV)	Mid-long-range issues	EuroNCAP AEB Protocol	Better mid-long-range detection than LiDAR-only
[5]	Rossi et al., 2021	Cooperative Fusion	Vehicle Network + LiDAR	Out-of-sight Object Detection	Data load in dense networks	Field Data	Improved occluded object recognition
[6]	Dasgupta et al., 2022	Hybrid Fusion	GNSS + Accelerometer + Speed Sensor	GNSS Spoofing Detection	Real-world complexity, sensor sync	Spoofing Test Scenarios	High detection rate in test scenarios
[7]	Zhong et al., 2022	Error Identification	Multi-sensor ADAS Setup	ADAS Fault Detection	Scalability, computational cost	Simulation/Custom	Detected 153 ADAS faults reliably
[8]	Sidhu et al., 2021	Configurable Framework	Multi-sensor Low-density Setup	Generic Sensor Fusion	High precision calibration	Field Test	Effective on low-cost, low-density sensors
[9]	Andert and Shrivastava, 2022	Tiered Fusion	Multi-vehicle Sensor Fusion	Multi-vehicle Localization	Scaling, high sensor accuracy demand	Miniature AV Testbed	Improved RMSE through adaptive error estimation
[10]	Yu et al., 2022	Delay-resilient Fusion	Vehicle Network Sensors	Delay-Compensated Tracking	Urban performance not validated	Controlled Simulations	Effective low-latency state estimation in controlled setup
[11]	Alyaprak and Gökmen, 2023	Multi-Sensor Fusion	Accelerometer + Temp Sensor	Vehicle Condition Monitoring	High computation, hard to generalize	Custom Dataset	High anomaly detection accuracy, but real-time load is high
[12]	Ligocki and Jelínek, 2022	Open-source Platform	LiDAR + Camera + GPS	Sensor Fusion Framework (Atlas Fusion)	ROS compatibility, resource demands	Not Specified	Flexible integration; limited real-time capability
[13]	Dworak et al., 2024	Cross-Domain Fusion	Radar + Camera	3D Object Detection	Computational cost, spatial alignment	Custom Dataset	More efficient than traditional methods, robust in adverse weather
[14]	Pan et al., 2020	Deep Fusion	Accelerometer + Temp Sensors	AV Fault Diagnosis	High computational load	Custom Dataset	Effective in diverse fault scenarios; real-time deploy is challenging
[15]	Schieber et al., 2022	Pyramid Fusion (PyFu)	LiDAR + Camera	Dense 3D Mapping, Urban Perception	Sparse LiDAR, high computation	Custom Urban Dataset	High accuracy on small segmentation tasks
[16]	Malawade et al., 2022	Energy-Efficient Fusion	Dynamic Multi-Sensor Setup	Low-Power AV Applications	Environmental tuning, high-res data handling	Not Specified	Energy savings achieved with competitive accuracy
[17]	John and Mita, 2021	Deep Fusion + Skip	Radar + Thermal + Camera	Object Recognition in Low-Light	Real-time challenge, sensor placement	Custom Environment	Superior recognition accuracy in poor illumination
[18]	Tong et al., 2023	Embedded Fusion System	Multi-Sensor + Cloud Integration	Urban Navigation and Occlusion Handling	Slow on large data, hardware optimization	Field Test	High occlusion resilience; needs enhancement for large-scale systems
[19]	Karle et al., 2023	High-Speed Fusion	Radar + LiDAR + High-Speed Camera	Object Tracking in Racing AVs	Not tested on public roads	Racing Simulation	Accurate in high-speed tracking; sensitive to light/dust variations
[20]	Hyndhavi and Sri Kavya, 2021	Real-world Fusion	Radar + Camera	Vehicle Tracking in Urban Traffic	Real-time lag, sensor alignment	Urban Field Test	Improved target tracking under occlusions and dense traffic
[21]	Zeng et al., 2022	DCNN-Based Fusion	Radar + Camera	Object Categorization	Computational complexity, real-world conditions	Custom Urban Dataset	High accuracy for small objects; real-time use limited by computation
[22]	Florea et al., 2022	Semantic-Geometric Fusion	Camera + LiDAR	3D Scene Perception	Sensor alignment, high computation	Urban Test Dataset	Accurate object distinction; not real-time feasible

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[23]	Billington et al., 2024	V2V Cooperative Fusion	AV Sensors + Traffic Surveillance Cameras	Enhanced Perception via Communication	Infrastructure dependency, high network traffic	Simulations + Field Test	High detection accuracy in low-GPS zones; reliant on camera density
[24]	Alaba, 2024	Adaptive Sensor Fusion	GNSS + IMU + ESKF + PSO-Tuned FLC	Urban Navigation in GPS-Degraded Areas	Sensitive calibration, sensor limitations	Urban Field Trials	High trajectory precision in complex terrains
[25]	Broedermann et al., 2022	Probabilistic Fusion	Camera + LiDAR	Explainable Localization	Computational load, real-time issues	Urban Dataset	Enhanced urban positioning; interpretability improved
[26]	Chen et al., 2022	Onboard–Offboard Fusion	LiDAR + Radar + Camera + Infra Surveillance	4D Object Detection, Confident Navigation	Weather effect on cameras, camera scarcity	Field Test and Simulations	Robust in GPS-denied zones; strong for infrastructure-aided AV
[27]	Agand et al., 2023	Adaptive Fusion (ESKF+FLC)	Radar + IMU + PSO-Fuzzy	Precise Trajectory Estimation	Terrain sensitivity, sensor tuning	Urban + Offroad Trials	Effective in real-time with better than Kalman-based approaches
[28]	Dai et al., 2023	Vision-Radar Fusion (ADAS)	Radar + Vision	Robust Vehicle Tracking in ADAS	Calibration and glare/rain sensitivity	MATLAB Simulations	Improved tracking accuracy over radar-only; stable in complex scenarios
[29]	Kunjumon and Gopan S, 2021	Kalman Filter Fusion	LiDAR + Camera	Object Tracking + Segmentation	Calibration-sensitive, dynamic issues	Lab Conditions	Increased precision; misalignment risks high in dynamic scenarios
[30]	Senel et al., 2023	Multi-Modal Object Tracking	Radar + LiDAR + Camera	Real-Time Multi-Object Tracking	Synchronization, computation demand	Complex Environment	Accurate in occlusion and crowd; system load needs optimization
[31]	Zhou et al., 2023	Imitation Learning Fusion	LiDAR + Camera	Driving Behavior Imitation for AVs	Training data quality, lighting/weather issues	Simulation Dataset	High simulation accuracy; limited generalizability to real-world conditions
[32]	Ignatious et al., 2023	Multi-Stage Fusion	Camera + Radar + LiDAR	End-to-End Decision Making	High computational cost, sensor sync	Urban Complex Dataset	Efficient in path planning; needs real-time optimization
[33]	Duan, 2024	Review-Level Fusion Summary	Various Sensor Fusion Types	Object Detection, Mapping, Localization	Real-time high-dimensional data handling	Multi-study Review	N/A – Survey Paper
[34]	Singh, 2023	Transformer-Based Fusion	LiDAR + Radar + Camera	Object Detection and Tracking	High resource demand, limited real-world application	Comparative Review	High detection potential; not yet practical for real-time AVs
[35]	Mendez et al., 2021	Lightweight Spectral Fusion	Camera + LiDAR (Edge Devices)	Robust Perception on Edge Hardware	Dense data limits, algorithm scalability	Control Experiments	Accurate on edge devices; improvement needed for complex scenes
[36]	Wozniak et al., 2023	Fault-Tolerant Fusion	Radar + LiDAR + Camera	Perception Resilience to Corruption	Computational load, real-time concerns	Simulation Tests	High robustness; safe-by-design useful in noisy environments
[37]	Tibebu et al., 2022	Probabilistic Interpretive Fusion	Camera + LiDAR	Explainable Localization in Urban AVs	High computational cost	Urban Test Cases	Improved positioning; beneficial for AVs needing interpretability
[38]	Hasanujjaman et al., 2023	Onboard + Offboard Fusion	AV Sensors + Traffic Surveillance Cameras	Detection and Navigation in GPS-denied Areas	Camera density, poor weather impact	Simulation + Live Trials	Strong in tunnels/underpasses; limited where traffic cameras absent
[39]	Moein and Tabatabaei, 2022	Adaptive Fuzzy-PSO Fusion	Radar + IMU + ESKF + FLC	Real-Time Urban Navigation	Calibration and tuning sensitivity	Urban Field Testing	High accuracy on trajectory; strong alternative in GPS-deprived areas
[40]	Wu et al., 2018	VTS Sensor Fusion for ADAS	Radar + Vision	Enhanced Tracking for ADAS	Calibration precision, high computational needs	MATLAB Simulations	Improved stability in highway-like scenarios; real-time use challenging

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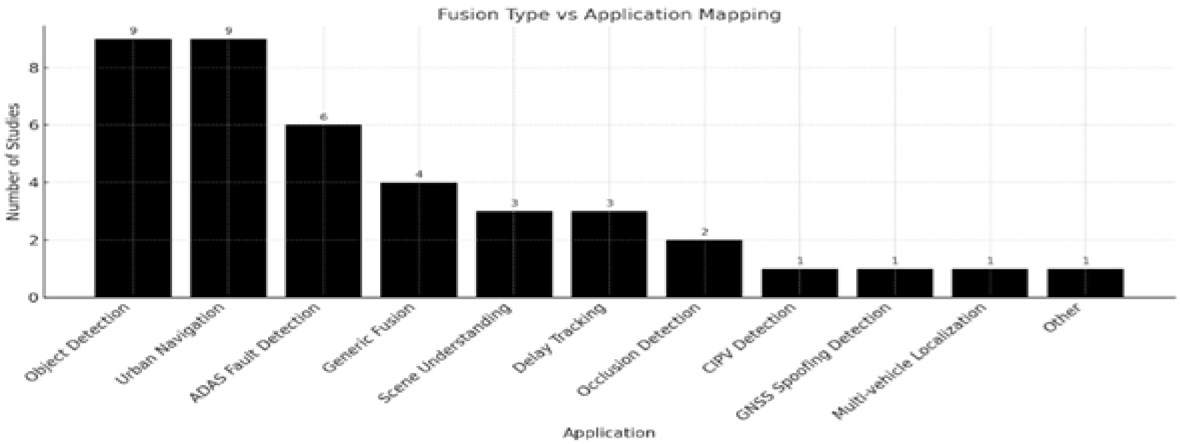

Fig. 1. Fusion Type Vs Application Mapping

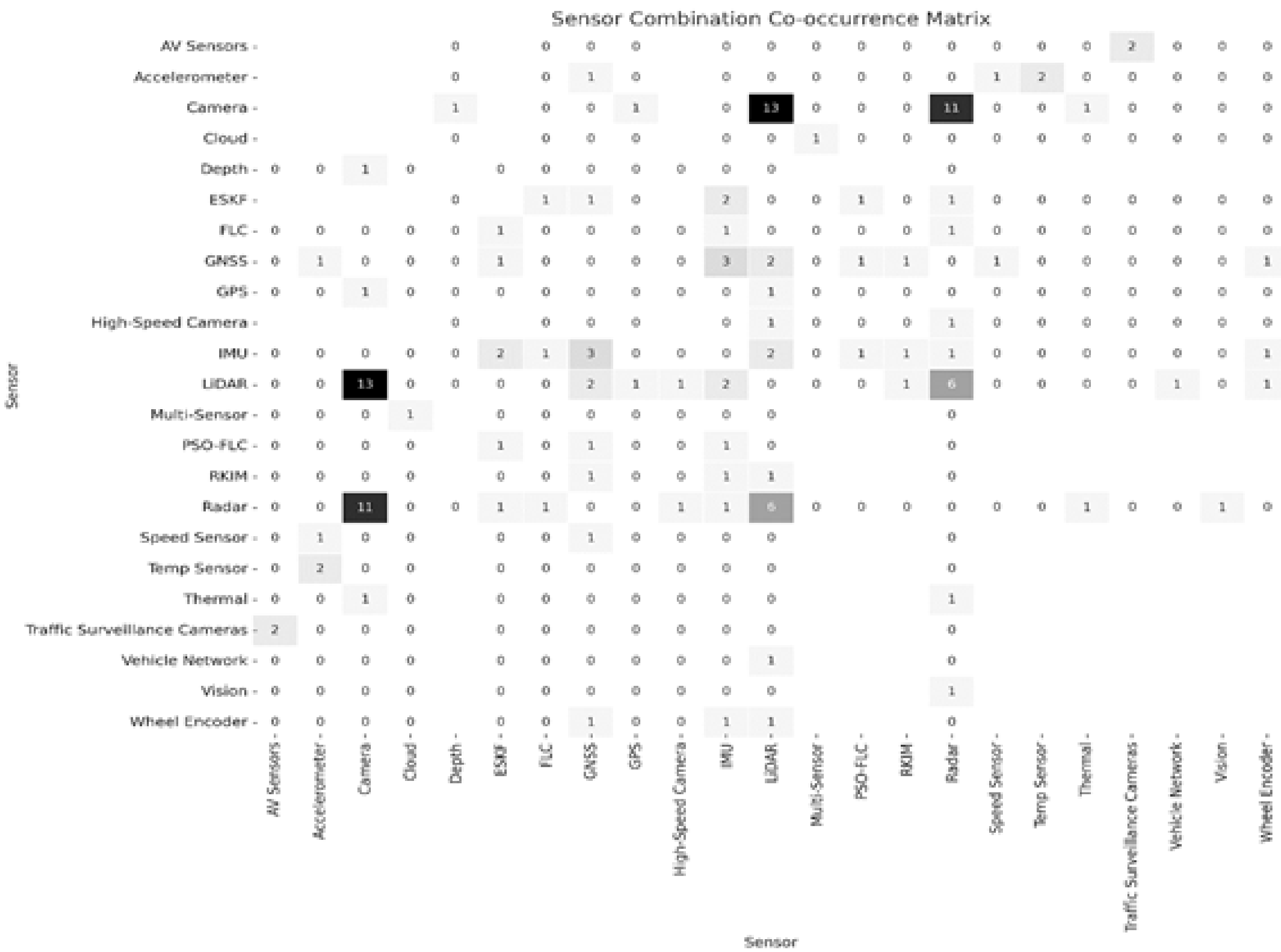

Fig. 2. Sensor Combinations Frequency

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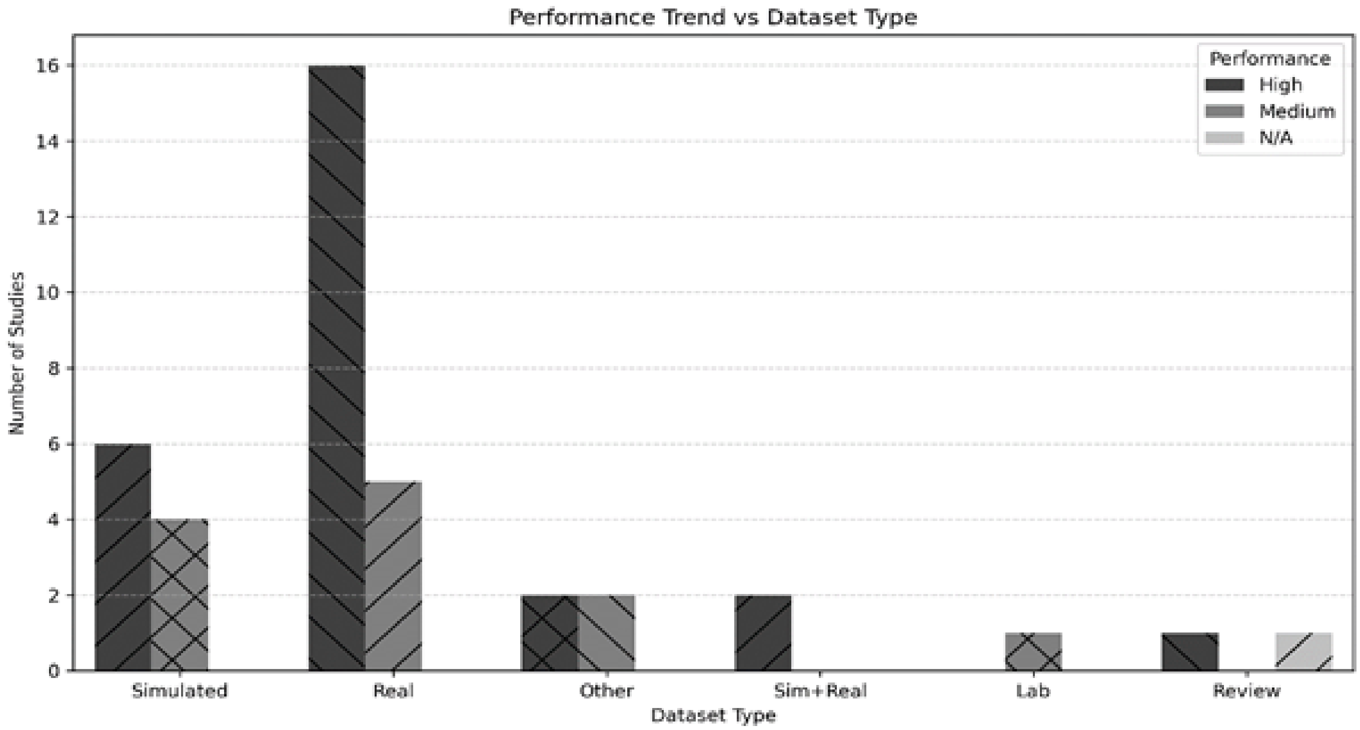

Fig. 3. Performance Trend vs Dataset Type

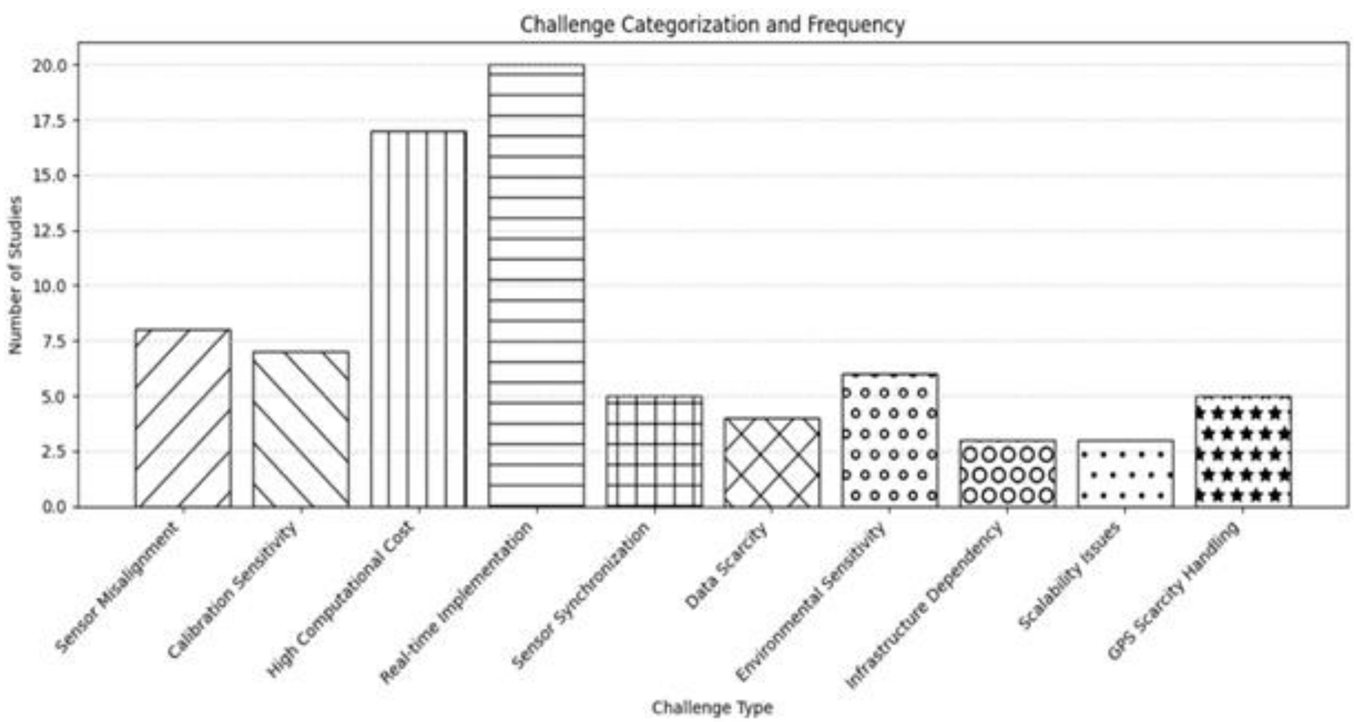

Fig. 4. Fusion Type Vs Application Mapping

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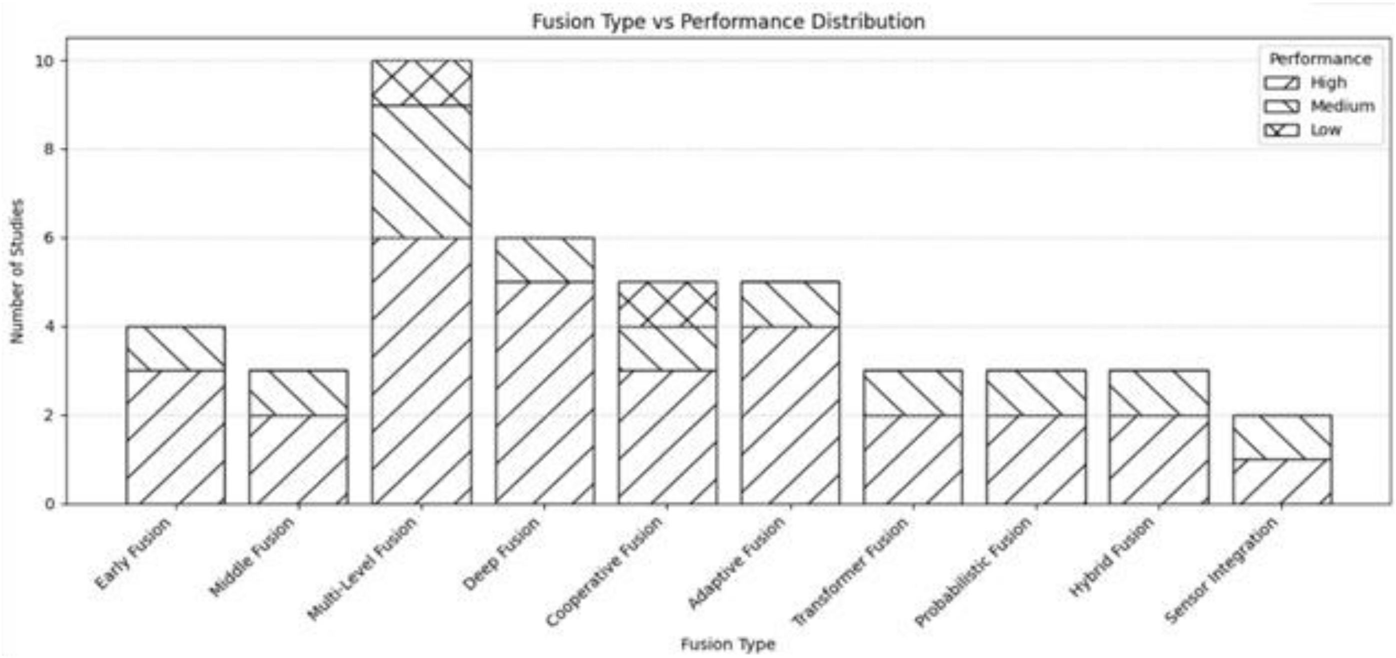

Fig. 5. Fusion Type vs Performance Distribution

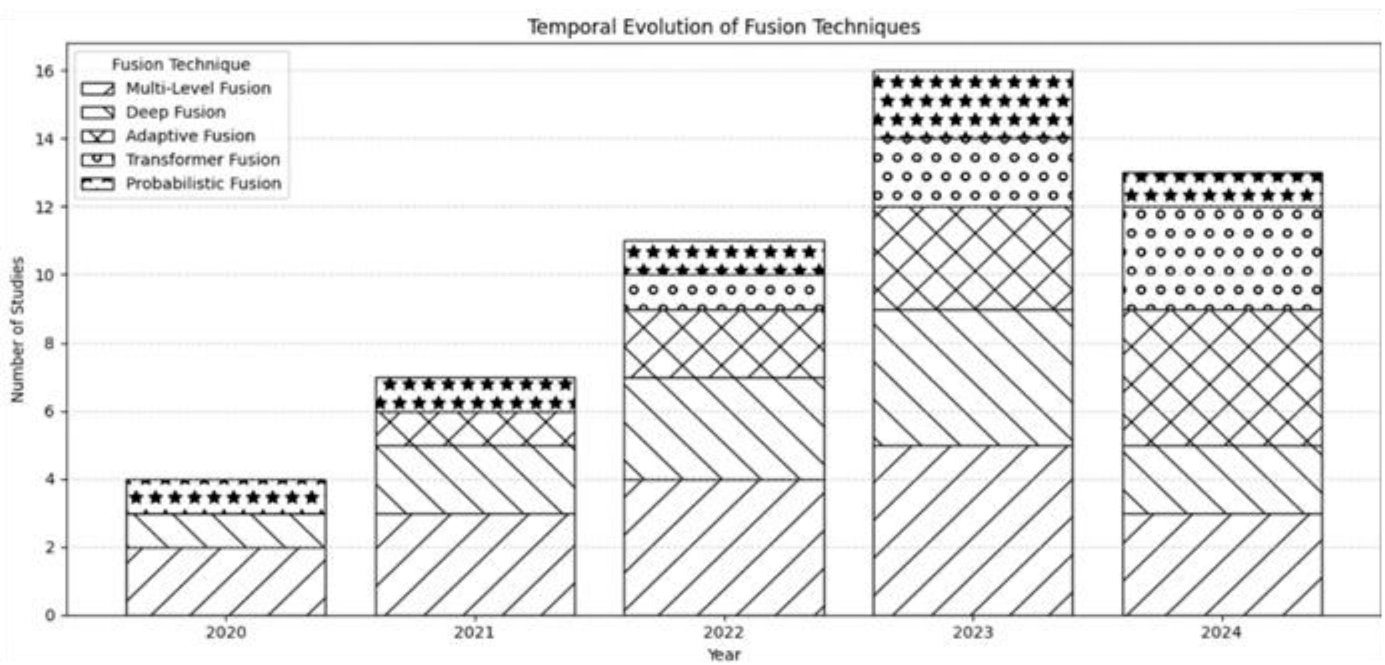

Fig. 6. Temporal Evolution of Fusion Techniques

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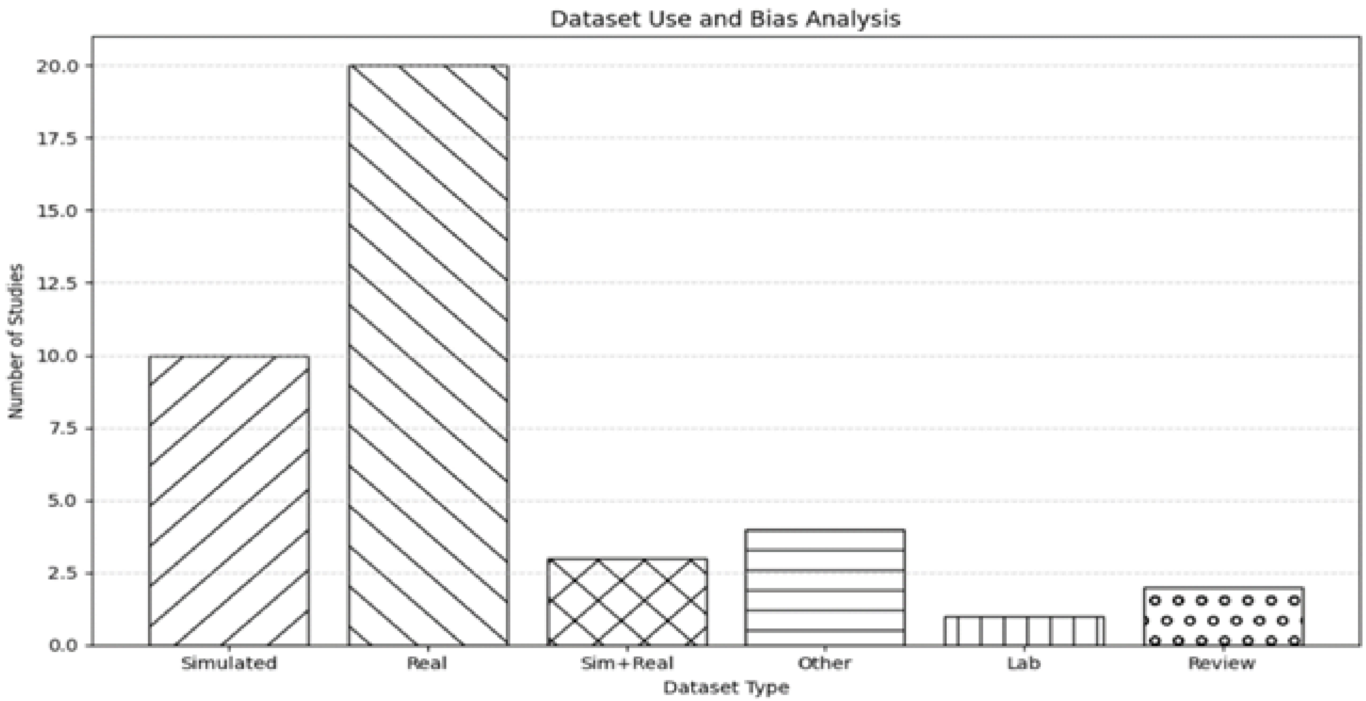

Fig. 7. Dataset Use and Bias Analysis

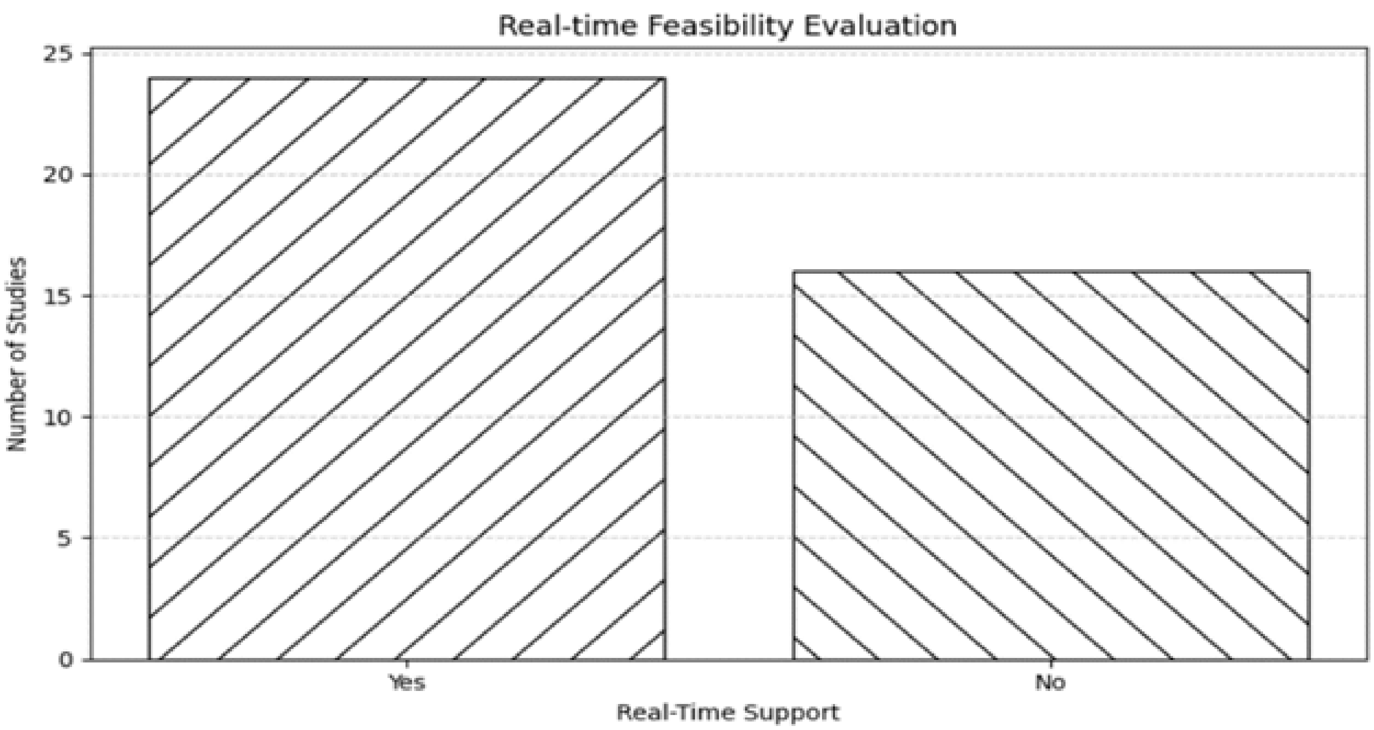

Fig. 8. Real-time Feasibility Evaluation

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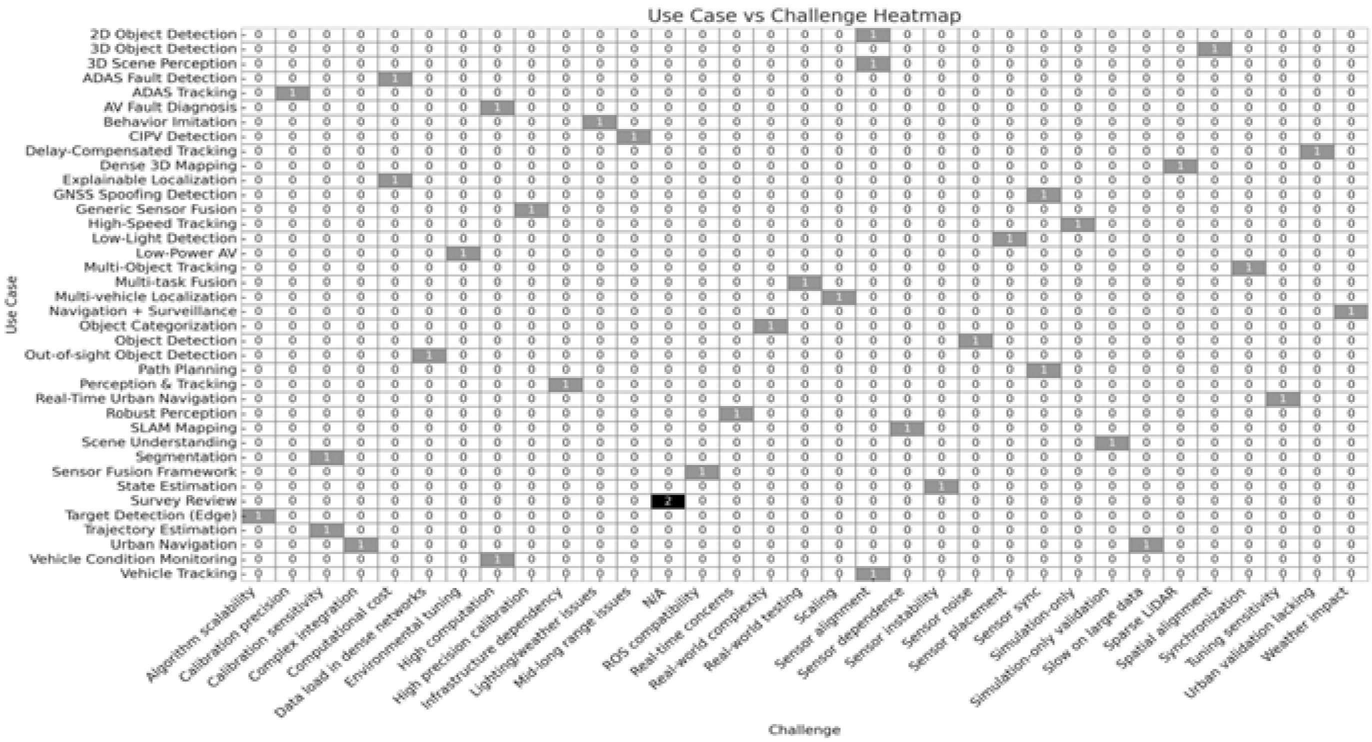

Fig. 9. Use Case vs Challenge Heatmap

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