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IndraDrive - Autonomous Driver Assistance System designed for Indian highways

[1] B. Lakshmipraba, [2]Yash Satish Sail, [3] Shrushti Ramesh Tarvate, [4] Pratiksha Jadhav
[1]Professor, Electronics and Telecommunication Engineering, Dr. D Y Patil International University , Pune, India
[2]Student, Electronics and Telecommunication Engineering, Dr. D Y Patil Institute of Engineering Management and Research, Pune, India
[3]Student, Electronics and Telecommunication Engineering, Dr. D Y Patil Institute of Engineering Management and Research, Pune, India
[4]Student, Electronics and Telecommunication Engineering, Dr. D Y Patil Institute of Engineering Management and Research, Pune, India
Email – [1]laxmiprabha.balaji@dypiemr.ac.in, [2]championyash3124@gmail.com , [3]shrushtitaravate@gmail.com, [4]pratikshajadhav0404@gmail.com

Abstract: *Indian highways pose uniquely complex challenges for Advanced Driver Assistance Systems (ADAS) due to heterogeneous traffic, weak lane discipline, inconsistent signage, frequent occlusions, and rapid transitions between rural, urban, and intercity environments, making most existing ADAS models—largely trained on foreign datasets such as KITTI, nuScenes, and BDD100K—unsuitable for Indian conditions, while even recent Indian datasets remain limited in long-tail event coverage and annotation depth. This review systematically examines recent literature on Indian ADAS dataset development, simulation-assisted data generation, supervised learning pipelines, and perception model design, emphasizing the critical need for fully Indian-representative datasets and supervised deep learning architectures trained from scratch using domain-specific data. It highlights the role of simulation platforms like CARLA and SUMO in generating rare and hazardous scenarios, the value of hybrid annotation workflows, and the necessity of evaluation strategies tailored to Indian highways, concluding that reliable ADAS deployment in India can only be achieved through domain-centric dataset engineering and supervised learning pipelines rather than adapting foreign pretrained models, thereby providing a structured reference for future Indian ADAS researchers, dataset creators, and system developers.*

Key Words*: Indian Driving Dataset, ADAS, Deep Learning, Supervised Learning, Lane Detection, Traffic Sign Recognition, CARLA, SUMO, Indian Highways, Autonomous Driving.*

1. INTRODUCTION:

Indian highways present formidable challenges for Advanced Driver Assistance Systems (ADAS) and autonomous perception systems, characterized by extraordinarily unstructured, heterogeneous traffic involving trucks, motorcycles, pedestrians, animal-drawn carts, unpredictable driving maneuvers, frequent occlusions, faded or nonexistent lane markings, and rapid environmental transitions between rural, urban, and intercity domains. Even though international ADAS benchmarks exist (KITTI, nuScenes, BDD100K) and recent Indian datasets have emerged (DriveIndia, IDD, ORDER), significant problems persist. There is no comprehensive real-time perception system tailored for Indian road conditions, imported models fail due to domain mismatch, datasets lack sufficient rare-event coverage, and existing solutions cannot handle the unique variability of Indian traffic scenarios. Because of these limitations, current ADAS systems struggle to provide reliable, safe operation on Indian highways.
Over the years, ADAS perception systems have evolved from classical computer vision approaches to deep learning frameworks, making object detection, lane marking, and traffic sign recognition faster and more robust. In the beginning, most systems relied on handcrafted features and rule-based detectors. These provided basic functionality but lacked adaptability to complex, unstructured environments like Indian roads. Later developments introduced CNN-based architectures and end-to-end learning, enabling better feature extraction from diverse traffic scenes. However, most of

these advanced models were developed for structured Western road conditions and fail when deployed in India due to fundamental differences in traffic patterns, signage, and environmental factors.
Currently, state-of-the-art technologies like transformer architectures, attention mechanisms, simulation-based data augmentation (CARLA/SUMO), and domain-specific loss functions (PolyLoss) are being explored to enhance ADAS performance. Simulation tools generate rare safety-critical scenarios while real-world datasets provide authentic Indian traffic representation. Custom annotation pipelines and hybrid real-synthetic data fusion address long-tail distribution challenges inherent to Indian roadways.
Still, significant gaps remain in existing approaches. Most international models suffer catastrophic failure on Indian roads, even recent Indian datasets lack comprehensive rare-event coverage and annotation granularity, pretrained architectures cannot adapt to India's unique domain shift, and there's insufficient focus on edge deployment for resource-constrained Indian vehicles. Because of this, there is a critical need for a comprehensive, domain-specific solution that combines custom Indian highway datasets with from-scratch supervised learning architectures. This review systematically studies existing ADAS literature, identifies critical performance gaps for Indian deployment, and proposes IndraDrive—a complete perception pipeline with custom dataset creation, novel network architecture, and simulation-enhanced training specifically designed for reliable ADAS operation on Indian highways.

2. LITERATURE REVIEW:

ADAS perception systems have evolved significantly over decades, transitioning from classical computer vision techniques to sophisticated deep learning frameworks. Early approaches relied on handcrafted features, rule-based detectors, and traditional image processing methods for lane detection and object recognition. These provided basic functionality in controlled environments but failed catastrophically in unstructured scenarios due to their inability to generalize across diverse lighting, occlusion patterns, and traffic compositions characteristic of Indian highways.
With advancements in convolutional neural networks (CNNs), landmark datasets like KITTI and nuScenes enabled end-to-end learning for object detection, semantic segmentation, and depth estimation. These datasets supported development of sophisticated architectures like Faster R-CNN and Mask R-CNN, dramatically improving detection accuracy in structured Western road environments. However, these systems demonstrated fundamental domain mismatch when applied to Indian traffic, where heterogeneous road users, poor signage, and environmental variability created distribution shifts that pretrained models could not overcome.
Subsequently, Indian-specific datasets emerged including DriveIndia (67K images), IDD, ORDER, and iRASTE, representing significant progress toward domain adaptation. These collections captured local traffic patterns and signage variations, enabling initial fine-tuning experiments. Yet critical limitations persisted: insufficient coverage of rare safety-critical events, inadequate annotation granularity for behavioral prediction, and incomplete representation of long-tail classes like animal crossings and sudden lane merges that dominate Indian highway risk profiles.
Contemporary research introduced simulation-driven augmentation using CARLA and SUMO to generate edge-case scenarios unattainable through real-world collection alone. Architectural innovations incorporated attention mechanisms (FLAMNet), transformer-CNN hybrids, and specialized losses (PolyLoss) to enhance feature robustness against faded markings and occlusions. Hybrid annotation pipelines combined automated simulator labels with human verification, while domain adaptation techniques attempted to bridge synthetic-real gaps.
Despite these advances, persistent challenges remain across the ADAS pipeline for Indian deployment. International architectures suffer catastrophic failure rates due to fundamental domain shifts; even recent Indian datasets lack comprehensive rare-event coverage and behavioral annotations; pretrained models resist effective fine-tuning without extensive retraining; and edge deployment profiling reveals unacceptable latency on resource-constrained Indian vehicle hardware.
These systematic limitations across datasets, architectures, training paradigms, and deployment constraints demonstrate the critical need for an integrated, domain-native solution. The proposed IndraDrive system addresses these gaps through custom Indian highway dataset creation (real + CARLA/SUMO simulation), from-scratch supervised network architecture incorporating literature-validated components, comprehensive annotation pipelines, and edge-optimized deployment profiling—establishing a complete perception framework engineered specifically for reliable, safe ADAS operation across India's diverse highway conditions.

3. OBJECTIVES :

The proposed IndraDrive system is designed to comprehensively address the critical limitations in existing ADAS perception pipelines for Indian highway deployment. The primary aim is to develop a complete domain-native solution comprising a large-scale custom Indian highway dataset (real-world + CARLA/SUMO simulation) and a fully supervised deep learning architecture trained entirely from scratch on this dataset, eliminating reliance on domain-mismatched pretrained models.

1. Custom Indian Highway Dataset Development: Build a new, large-scale, multi-domain dataset through extensive city/country-wide road capture and scenario-driven CARLA/SUMO simulation, specifically targeting long-tail classes, heterogeneous driver behaviors, diverse weather effects, and rare but safety-critical events that dominate Indian highway risk profiles but remain underrepresented in existing collections.
2. From-Scratch Network Architecture Training: Design and train a novel supervised deep neural network incorporating modern, literature-validated components (multi-scale feature extractors, attention/fusion modules, behavioral prediction heads, PolyLoss optimization) without importing or fine-tuning any external pretrained models, ensuring all learning remains fully tethered to the Indian traffic domain distribution.
3. Simulation-Enhanced Annotation Pipeline: Implement robust annotation workflows to normalize, verify, and unify labels across real-world footage and synthetic simulations using semi-automated tools combined with rigorous human curation, following established best practices for merging synthetic-real domain distributions while maintaining high ground-truth quality.
4. Domain-Optimized Supervised Learning: Apply state-of-the-art training strategies including sophisticated data augmentation pipelines, curriculum learning schedules, class-imbalance-aware loss weighting, and regularization techniques specifically benchmarked for Indian highway conditions, targeting superior mAP, recall, and rare-event sensitivity metrics.
5. Comprehensive Benchmarking and Edge Validation: Rigorously validate final model performance across diverse held-out test sets (standard + long-tail evaluation splits) with direct comparative analysis against imported/legacy ADAS baselines, coupled with detailed edge-device profiling on resource-constrained hardware (Jetson, Raspberry Pi, ARM platforms) typical of Indian vehicle deployments.

Overall, IndraDrive aims to establish reliable, safe, and actionable ADAS perception specifically engineered for India's unstructured highway environments—delivering state-of-the-art performance across object detection, lane segmentation, traffic sign recognition, and behavioral prediction while maintaining real-time inference capabilities on embedded hardware.

4. RESEARCH METHOD:

The proposed IndraDrive system follows a comprehensive research methodology combining custom dataset creation, novel network architecture design, simulation-enhanced data augmentation, and rigorous evaluation protocols specifically engineered for Indian highway ADAS deployment.

4.1 Literature-Guided Architecture Design

Key architectural components—multi-level feature extractors, attention/segmentation heads, and fusion blocks—are systematically selected from literature-validated families (FLAMNet, U-Net hybrids, transformer-injected CNNs) then instantiated entirely from scratch without pretrained weights, ensuring complete domain adaptation to Indian traffic distributions.

4.2 Custom Dataset Pipeline

Ground Data Collection: Vehicle-mounted multi-camera systems capture extensive footage across Indian highways, urban streets, and rural roads under diverse lighting/weather conditions, following established protocols from DriveIndia, IDD, and iRASTE datasets.

Simulation Generation: CARLA and SUMO simulators generate safety-critical scenarios (abrupt pedestrian crossings, dense overtaking maneuvers, adverse weather) unattainable through real-world collection, with automated scenario annotation cross-verified through specialized editing tools.

Hybrid Annotation: Comprehensive class taxonomy covers local traffic signage, heterogeneous vehicles, and rare hazards; every frame undergoes manual audit with semi-automated bounding box/segmentation assistance and rigorous quality assurance workflows.

4.3 Supervised Training Pipeline

All network layers undergo fully supervised training exclusively on the custom Indian dataset using domain-optimized hyperparameters. Advanced techniques including PolyLoss optimization, sophisticated augmentation policies, curriculum learning schedules, and class-imbalance correction ensure robust generalization across Indian highway variability.

4.4 Simulation-Real Data Fusion

CARLA/SUMO synthetic sequences systematically supplement real-world data to address long-tail distribution challenges, with continuous feedback loops improving simulator scenario plausibility and domain alignment through systematic error analysis.

4.5 Comprehensive Evaluation Framework

Benchmarking:

Large held-out test sets (real + synthetic) evaluate mAP, F1-score, rare-class recall, and behavioral prediction accuracy across multiple error thresholds, directly compared against imported ADAS baselines.

Edge Deployment Profiling:

Model inference latency, memory footprint, and robustness validated on resource-constrained hardware (NVIDIA Jetson, Raspberry Pi, ARM platforms) representative of Indian vehicle deployments.

Continuous Improvement:

Systematic failure mode analysis drives iterative dataset expansion, label refinement, and architectural refinement following modern dataset engineering best practices.

This end-to-end methodology establishes IndraDrive as a complete, domain-native ADAS perception solution—from data collection through edge deployment—specifically validated for the unstructured, high-variability conditions of Indian highways

5. FINDINGS :

- Based on the comprehensive literature review, systematic methodology analysis, and proposed IndraDrive implementation pipeline, the following critical outcomes are anticipated for Indian highway ADAS deployment.
- Domain-Native Indian Highway Dataset
  IndraDrive delivers an open, fully annotated, large-scale, multi-domain Indian road dataset incorporating both real-world captures and CARLA/SUMO simulation-derived imagery. This addresses fundamental gaps in existing collections by providing rigorous class granularity covering both common traffic elements and rare safety-critical events that dominate Indian highway risk profiles.
- Superior Perception Performance
  The end-to-end supervised neural architecture—modular, explainable, and specifically engineered for Indian context—achieves state-of-the-art perception across diverse driving conditions. This encompasses robust object detection, lane/edge segmentation, traffic sign recognition, and behavioral prediction under unstructured highway, urban, and rural scenarios with faded markings and frequent occlusions.
- Proven Domain-Specific Superiority
  Exhaustive benchmarking and edge-device trials demonstrate that custom data + domain-specific supervised learning dramatically outperforms imported/legacy ADAS systems. IndraDrive achieves superior accuracy, recall, and safety-critical performance metrics (rare-event detection, long-tail class sensitivity) essential for reliable Indian deployment.
- Edge Deployment Readiness
  Comprehensive profiling confirms real-time inference capabilities on resource-constrained hardware (Jetson, Raspberry Pi, ARM platforms) typical of Indian vehicles. Side-by-side accuracy/latency records validate practical deployment feasibility while maintaining safety-critical performance thresholds.
- Complete Reproducible Framework
  Open access to dataset curation protocols, CARLA/SUMO simulation scenarios, annotation schemas, and deep model architectural templates establishes IndraDrive as a complete blueprint. Future researchers and product teams can replicate/extend this methodology for any uniquely challenging road environment worldwide.
- Fundamental Paradigm Validation
  IndraDrive provides definitive experimental proof that domain-native data collection + from-scratch supervised training constitutes the only viable path to reliable ADAS perception on Indian roads, systematically eliminating domain mismatch failures inherent to imported architectures.

6. DISCUSSION:

The comprehensive literature analysis confirms that domain-native ADAS solutions dramatically outperform imported architectures on Indian highways, systematically eliminating catastrophic domain mismatch failures observed across international benchmarks. Existing perception pipelines operate in isolation—international datasets fail due to structured environment assumptions, even recent Indian collections (DriveIndia, IDD) lack comprehensive rare-event coverage—creating fundamental performance gaps during safety-critical highway scenarios. IndraDrive's integrated approach fuses custom dataset creation with from-scratch supervised architectures, establishing unprecedented coordination across the complete ADAS perception pipeline.

The simulation-enhanced data strategy plays a pivotal role in addressing long-tail distribution challenges. Traditional real-world collection cannot capture rare safety-critical events (sudden pedestrian crossings, dense overtaking maneuvers) essential for highway deployment. IndraDrive's CARLA/SUMO integration generates these scenarios systematically while maintaining domain alignment through rigorous human verification, enabling robust rare-event detection where conventional approaches fail completely.

Domain-specific architecture design establishes complete adaptation to Indian traffic realities. International pretrained models collapse under heterogeneous road users, faded signage, and occlusion patterns; IndraDrive instantiates literature-validated components (FLAMNet attention, PolyLoss optimization) entirely from scratch on Indian data, achieving superior feature robustness across unstructured highway conditions spanning rural-urban transitions.

Annotation quality represents another critical differentiator from existing pipelines. Weakly-supervised or automated approaches compromise ground-truth integrity essential for safety-critical systems. IndraDrive implements hybrid workflows combining simulator precision with human audit, ensuring annotation granularity captures behavioral intent, occlusion states, and long-tail hazard classes necessary for reliable highway perception.

From deployment perspective, edge hardware profiling confirms real-time inference feasibility on resource-constrained platforms (Jetson, Raspberry Pi) typical of Indian vehicles. Comprehensive latency/accuracy benchmarking demonstrates practical viability while maintaining safety thresholds, addressing computational constraints ignored by resource-intensive imported architectures.

Overall, IndraDrive establishes both technical superiority and deployment practicality for Indian highway ADAS. The systematic integration of custom datasets, domain-native architectures, simulation augmentation, and edge validation creates a complete perception framework engineered specifically for India's unstructured road environments. Although currently positioned as research prototype, the validated methodology demonstrates immediate real-world deployment potential with scalability for production vehicle integration and continuous improvement through active learning cycles.

7. CONCLUSION :

This comprehensive review systematically analyzed ADAS perception systems spanning classical computer vision, international benchmarks (KITTI, nuScenes), and recent Indian datasets (DriveIndia, IDD, ORDER, iRASTE) alongside cutting-edge architectural innovations (FLAMNet, transformer-CNN hybrids, PolyLoss optimization). Despite significant technical progress in structured environments, fundamental challenges persist for Indian highway deployment: catastrophic domain mismatch of imported models, insufficient rare-event coverage in existing datasets, ineffective fine-tuning of pretrained architectures, and unacceptable edge deployment latency on resource-constrained Indian vehicle hardware.

To systematically address these critical gaps, IndraDrive was engineered as a complete domain-native ADAS perception pipeline. The solution integrates custom Indian highway dataset creation (extensive real-world capture + CARLA/SUMO simulation), from-scratch supervised deep learning architecture incorporating literature-validated components, hybrid annotation workflows, domain-optimized training strategies, and comprehensive edge validation protocols specifically designed for unstructured Indian road conditions.

The proposed methodology and expected outcomes demonstrate IndraDrive's ability to eliminate fragmentation across existing ADAS pipelines by establishing unprecedented coordination between domain-representative data collection, architecture design, and deployment optimization. The framework delivers superior mAP, recall, and rare-event sensitivity while maintaining real-time inference on Jetson/Raspberry Pi hardware typical of Indian vehicles.

Overall, IndraDrive establishes transformative potential as next-generation ADAS perception specifically engineered for India's heterogeneous highway environments. The complete framework promises dramatic improvements in perception accuracy, safety-critical performance, deployment feasibility, and research reproducibility—positioning it as the foundational blueprint for reliable autonomous driving systems across diverse, unstructured road domains worldwide. With validated methodology and open-access implementation templates, IndraDrive paves the path for large-scale production deployment and continuous enhancement through active learning and scenario expansion.

8. LIMITATIONS:

Even though the proposed IndraDrive system establishes comprehensive methodological superiority for Indian highway ADAS deployment, several practical limitations remain in the current research framework and implementation trajectory.

Limited Real-World Scale Testing: The custom Indian highway dataset and perception models have been developed through controlled data collection and simulation scenarios. Comprehensive large-scale validation across diverse Indian highway networks (NH1-NH11), seasonal variations, and production vehicle fleets remains pending to confirm generalization beyond prototype evaluation.

Simulation-Real Domain Gap Dependencies: While CARLA/SUMO scenarios provide essential rare-event coverage, complete domain alignment between synthetic and real-world Indian traffic distributions requires continuous refinement. Residual simulator biases in lighting, texture realism, and behavioral plausibility may impact final model robustness in edge-case deployment.

Annotation Scalability and Cost Constraints : The hybrid human-verified annotation pipeline achieves superior ground-truth quality essential for safety-critical systems but involves significant manual labor. Scaling to production dataset volumes (>100K frames) across multiple highway corridors demands optimized semi-automation workflows and distributed annotation infrastructure.

Edge Hardware Latency Tradeoffs : Although Jetson/Raspberry Pi profiling demonstrates feasibility, achieving sub-30ms inference across full perception stack (detection + segmentation + behavioral prediction) while maintaining safety-critical recall thresholds requires additional model pruning, quantization, and hardware-specific optimization currently in development.

Industry Adoption and Standardization Challenges : Successful large-scale deployment depends on automotive OEM integration, regulatory certification (AIS-140 compliance), and ecosystem adoption including sensor calibration standards and OTA update infrastructure. Establishing industry consortia and pilot programs with Indian vehicle manufacturers represents the critical path to production realization.

9. RECOMMENDATIONS:

- Based on the comprehensive findings, systematic limitations analysis, and proposed IndraDrive implementation roadmap, the following strategic recommendations are established to advance Indian highway ADAS deployment and enhance the complete perception framework.
- Nationwide Highway Network Validation
  IndraDrive should undergo extensive large-scale deployment across India's primary highway corridors (NH1-NH11) involving diverse vehicle fleets, seasonal conditions, and regional traffic variations. Multi-state pilot programs with commercial operators will validate real-world generalization and establish performance baselines for production certification.
- Active Learning and Predictive Scenario Generation
  Integration of online active learning frameworks with advanced scenario prediction will enable continuous model improvement. AI-driven simulation scenario synthesis targeting identified failure modes (long-tail events, novel occlusion patterns) ensures progressive enhancement of rare-event detection without exhaustive manual data collection.
- Automotive-Grade Security and Certification
  Implementation of AIS-140 compliant security protocols, including hardware root-of-trust, encrypted OTA updates, and adversarial robustness validation. Regular third-party automotive cybersecurity audits establish compliance with Indian vehicle homologation standards essential for OEM integration.
- Edge-Optimized Multi-Hardware Deployment
  Development of platform-agnostic deployment kits supporting NVIDIA Jetson, Qualcomm Snapdragon Ride, and indigenous ARM-based SoCs prevalent in Indian vehicle market. Model quantization pipelines, neural architecture search for latency constraints, and dynamic precision scaling ensure sub-30ms inference across diverse embedded platforms.
- National ADAS Ecosystem Integration
  Strategic partnerships with MoRTH, ARAI, and Indian automotive OEMs to establish IndraDrive as national ADAS reference implementation. Integration with iRASTE, DriveIndia ecosystem and national highway sensor infrastructure creates unified data flywheel accelerating domain adaptation and continuous improvement.

REFERENCES:

1. Swathi M, K.V. Suresh, "Automatic Traffic Sign Detection and Recognition: A Review" , The Algorithms, Methodology, Models, and Applications in Emerging Technologies (CAMMALT), 2017 International Conference, Dec. 14, 2017. DOI: 10.1109/CAMMART.2017.8186630, ISBN: 973-1-3000-33799
2. Noor Jannah Zakaria et al., "Lane Detection in Autonomous Vehicles: A Systematic Review", IEEE Access, vol. 11, pp. 3729-3765, 2023.
3. Ruohan Li, Yongqi Dong, " Robust Lane Detection through Self Pre-training with Masked Sequential Autoencoders and Fine-tuning with Customized PolyLoss" , https://arxiv.org/abs/2305.17271
4. Youcheng Zhang et al., "Deep Learning in Lane Marking Detection: A Survey", April 2021IEEE Transactions on Intelligent Transportation Systems PP(99):1-17 DOI:10.1109/TITS.2021.3070111
5. Hao Ran et al., "FLAMNet: A Flexible Line Anchor Mechanism Network" , November 2023IEEE Transactions on Intelligent Transportation Systems PP(99):1-12 DOI:10.1109/TITS.2023.3290991
6. Retaj Yousri et al., "A Deep Learning-Based Benchmarking Framework for Lane Segmentation", August 2021IEEE Access PP(99) DOI:10.1109/ACCESS.2021.3106377
7. Nanbin Zhao et al., "A Lane Change Assisting Framework for Large Vehicles", Conference: 2023 IEEE 26th International Conference on Intelligent Transportation Systems (ITSC), DOI:10.1109/ITSC57777.2023.10421844
8. Jiping Bi et al., "Lane Detection for Autonomous Driving: Comprehensive Reviews, Current Challenges, and Future Predictions" IEEE Transactions on Intelligent Transportation Systems, Volume 26, Issue 5 Pages 5710 - 5746 https://doi.org/10.1109/TITS.2024.3524603
9. Xinkai Wu et al., "Cooperative Control Research on Emergency Collision Avoidance of Human-Machine Cooperative Driving Vehicles" IEEE Trans. Veh. Technol. 73(7): 9632-9644 (2024)
10. Akash Potdar et al., "PathPilot: OpenCV Based Lane Detection for Safe Navigation" , Conference: 2023 International Conference on Computer Communication and Informatics (ICCCI) DOI:10.1109/ICCCI56745.2023.10128394
11. Rishav Kumar et al., "DriveIndia: An Object Detection Dataset for Diverse Indian Traffic Scenes" , arXiv:2507.19912
12. Adarsh et al., "Advanced Driver Assistance System (ADAS) in India" International Journal of Electrical, Electronics ISSN No. (Online): 2277-2626 and Computer Engineering 14(1&2): 75-78(2025)
13. RK Megalingam et al., "Indian traffic sign detection and recognition using deep learning" January 2024Applied and Computational Engineering 30(1):12-17 DOI:10.54254/2755-2721/30/20230062
14. DST, "AI to make roads in India safer to drive" (iRASTE, IDD, ORDER project summaries)