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Road Width Estimation Using Multi Camera Deep Learning Framework in Unmarked Indian Roads: Quantitative Modeling for Economic Prediction

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Abstract

The accurate estimation of road widths on unmarked and un- structured roads is critical for Advanced Driver Assistance Systems (ADAS), autonomous navigation, and intelligent transportation plan- ning. In Indian driving conditions, irregular boundaries and missing lane markings make conventional lane detection ineffective. We pro- pose a multi-camera framework integrating a dashboard monocular camera with dual Outside Rear View Mirror (ORVM) cameras for dynamic road-width estimation. The scheme employs deep learning segmentation to extract road boundaries and fuses monocular depth and stereo disparity using a Kalman-based dynamic model. From a quantitative perspective, the recursive Kalman fusion functions anal- ogously to dynamic optimization and equilibrium modeling in 'Quan- titative Economics, allowing predictive analysis of traffic density, flow efficiency, and infrastructure utilization. Trained on a diverse ur- ban–rural Indian road dataset, the model achieves high estimation ac- curacy and predictive stability, demonstrating improved performance over single-camera baselines and enabling data-driven optimization for safe, efficient transportation systems.

Keywords: *Road Width Estimation, Dashcam System, Edge De Tection, Stereo Vision, Deep Learning, Sensor Fusion, Indian Roads, Advanced Driver Assistance Systems (ADAS)*

1.Introduction

Today, both Advanced Driver Assistance Systems (ADAS) and au- tonomous driving rely on a precise understanding of the geometry of the road to maintain a safe lane, overtake, and avoid collisions. However, in many emerging markets, including India, unmarked and irregular roads, dense mixed traffic, and frequent occlusions make lane-centric assumptions brittle. Recent reports indicate the rapid adoption of ADAS in India during 2025 and the increasing municipal deployments of AI dashcams, highlighting both the opportunity and the need for a perception tuned to local conditions Times of India (2025a,b); Hirt (1974). Technically, perception has advanced along three converging threads. First, lane/boundary understanding increasingly leverages transformer- based decoders and edge-efficient designs for real-time deployment Luo et al. (2025); Author and Coauthor (2025). Second, depth es- timation, critical for the metric reasoning on road width, has seen renewed interest in 2025 through evaluations and surveys that bench- mark monocular pipelines and discuss reliability under challenging optics Third, multisensor (and multiview) fusion continues to ma- ture, from principled taxonomies of data/feature / decision level fusion to new BEV and vision language paradigms oriented to robust driv- ing stacks Qian et al. Anonymous (2025). In addition, cost-effective sensor boundary sig- nals such as the 4D mmWave radar have emerged in 2025 as robust signals under adverse weather In this scheme, we consider the estimation of the width of the road on unmarked Indian roads using a dashcam configuration with three cameras (front monocular with dual cameras on the side). Mul- tiview imagery offers complementary perspectives for boundary con- tinuity where single-view methods struggle with occlusions and non- standard markings. Our contributions are: (i) a deployable multi- camera pipeline that fuses semantic road masks with monocular/stereo depth for metric width estimation; (ii) a design aligned with 2025 in- sights on efficient lane perception and fusion; and (iii) an evaluation on diverse Indian scenarios, motivated by current ADAS adoption and civic deployments [1-5].

1.1.Literature Review

Traditional edge/Hough/template methods degrade under occlusions, shadows, and worn marks Chen and Wang (2020). Deep CNN / RNN models capture spatial–temporal context while transformer-based lane prediction improves complex geometries Width estimation often uses stereo/ LiDAR; recent work integrates monocular depth with segmentation; Point-cloud/statistical methods Kukolj and Others (2021) and aerial graph-based detection Xu and Others (2021) support HD mapping but are not real-time in- vehicle [6-8].

1.2.Lane/Boundary Perception

Recent work emphasizes transformer decoders and hybrid CNN–CNN- Transformer pipelines that improve topology awareness and occlusion robustness while remaining deployable on the edge. A 2025 survey con- solidates 2D / 3D lane methods (segmentation/detection/parameterization) and generalization of benchmarks across data sets and weather, set- ing baselines for unmarked or weakly marked roads oriented variants and ensembles that mix CNN, SCNN, and Swin backbones further stabilize predictions in reduced visibility (for ex- ample, fog) and embedded hardware These trends are consistent with the lane/boundary module in our pipeline. Depth Estimation for Metric Reasoning Monocular depth remains attractive for low-cost ADAS, with 2025 syntheses discussing reliabil- ity, optics, and domain shifts such as night, rain, and mapping algo- rithmic choices to error modes Evaluations underline failure cases from reflective/ texture-poor sur- faces and suggest fusing monocular priors with auxiliary geometry. Tech reports likewise examine low-cost stacks for scene completion and width-related metrics in resource-constrained systems UC Berke- ley EECS (2025). These motivate our use of mono depth at the front view, complemented by stereo on the sides. Multi-Sensor / Multi-View Fusion and BEV A 2025 review in *Sen- sors* catalogs data/ feature/decision-level fusion, synchronization, cal- ibration, and uncertainty handling - highlighting BEV as a unifying representation for robust stacks Contemporary BEV works (BEVCon; progressive BEV) improve spatial consistency and occlusion handling using contrastive or curriculum strategies More broadly, vision language (ac- tion) surveys argue for modular perception tightly coupled to reason- ing and planning, which can help to adjudicate ambiguous boundaries in mixed traffic Jiang et al. (2025). Our design follows these findings by fusing multi-view camera cues into a consistent ego-frame with temporal smoothing. Cost-Effective Sensing for Boundary Cues Beyond cameras, 2025 reports introduce 4D mmWave radar for direct boundary detection (e.g. fences, bushes), showing robustness under adverse weather/lighting conditions - a known pain point for monocular methodsMoreover, our present prototype is camera-only; such radar can be integrated for fail-operational boundary priors in future itera- tions. Road-Width Estimation and Practice Context Direct road width estimation from dashcams appears sparsely covered; prior applied studies focus on width/hole measurement pipelines using commod- ity cameras, but with limited treatment of dense occlusions and mul- tiview fusion Author (2023). The 2025 adoption landscape (ADAS uptake; municipal AI dashcams) underscores the real-world need for robust, locally tuned perception on unmarked roads, aligning with our contributions and evaluation emphasis. Challenges on Indian Roads Indian Road scenes present sev- eral recurring challenges that undermine lane–centric assumptions and directly affect the estimation of the boundary and width. Missing / inconsistent lane markings: worn, absent, or impro- vised markings reduce the reliability of purely lane-based signals, forcing greater reliance on texture, curb/edge, and drivable-space signals.Irre gular, occluded boundaries: parked vehicles, roadside ven- dors, temporary barricades, vegetation, and debris frequently obscure true road edges, leading to fragmented or ambiguous boundary evidence. Variable geometries: frequent transitions between narrow lanes, undivided carriageways, encroachments, and informal shoulders create non-standard cross-sections that invalidate fixed-width priors. Dynamic obstacles: dense mixed traffic two-wheelers, pedestri- ans, animals, and slow-moving carts—introduces fast-changing occlusions and atypical trajectories that degrade single-view con- tinuity. Adverse lighting and weather: strong glare, low illumination, rain, fog, and water-logged surfaces reduce contrast and distort depth/edge cues, stressing both segmentation and depth estima- tion Background & Motivation Accurate environmental perception is the foundation for ADAS and autonomous driving. Road width es- timation underpins lane keeping, overtaking, and collision avoidance, yet conventional methods presuppose well-marked lanes and standard- ized infrastructure uncommon on Indian roads. Deep models with sensor fusion have improved perception in complex scenes Sanil and Others (2024), and municipal deployments demonstrate the feasibil- ity of AI-enabled dashcams in practice Times of India (2025). These factors motivate a multiview camera setup and late fusion of seman- tic masks with monocular & stereo depth to recover stable left/right boundaries despite occlusions and nonstandard geometry, while allow- ing temporal smoothing to handle short-lived disruptions. rganization of the Scheme. The remainder of this paper is structured as follows. Section 3 introduces the proposed multi-camera framework, outlining its design objectives, hardware configuration, and functional methodology, drawing inspiration from recent advances in lane perception and hybrid transformer-based segmentation models. Section 4 details the experimental setup, including the construction of the Urban–Rural Road Boundary Dataset (UR–RBD), training strat- egy, and implementation specifics, following standard practices in the estimation of road-width and depth evaluation. Section 5 presents quantitative and qualitative evaluations, comparative analysis with conventional monocular and stereo-based approaches, and ablation studies that validate the contribution of each fusion component. Sec- tion 6 summarizes key findings and discusses practical implications for the deployment of advanced driver assistance systems (ADAS) in Indian road environments, in line with contemporary fusion and per- ception frameworks. Finally, Section 7, concludes the scheme, empha- sizing the broader implications of the proposed system and outlining future directions such as temporal transformers, radar integration, and federated learning for scalable and intelligent transportation systems [9-15].

1.3. Proposed Approach

We present a forward-facing monocular dashcam with dual ORVM cameras to expand the field of view and provide multiperspective cues. Semantic segmentation delineates drivable space; monocular depth (front) and stereo disparity (sides) reconstruct road geometry; and a fusion layer integrates signals with temporal smoothing. Related fu- sion frameworks Malawade and Others (2022) and bidirectional fusion for road segmentation motivate our design. Objectives The proposed framework aims to achieve robust and real-time road-width estimation on unmarked Indian roads through a cost-effective multi-camera dashcam system. The specific objectives are as follows. *Design a multi-camera sensing configuration* that integrates a front monocular camera with dual ORVM-mounted cameras to capture various viewpoints and minimize occlusions. *Develop deep-learning models for segmentation and depth esti- mation* that are fine-tuned for Indian road conditions and varied illumination/ weather scenarios. *Implement a sensor-fusion mechanism* combining semantic seg- mentation, monocular depth, and stereo disparity with Kalman- based temporal smoothing for accuracy and stability. *Validate the complete system* on a comprehensive urban-rural data set (UR-RBD) that covers different terrains, lighting and traffic conditions to ensure deployability and robustness. Mathematical Modeling The Kalman-based fusion and re- gression components proposed in our framework can be interpreted within the paradigm of quantitative economics, where dynamic sys- tems are analyzed through mathematical and statistical modeling. The recursive estimation nature of the Kalman filter reflects a form of dynamic optimization and equilibrium modeling, commonly ap- plied in economic systems to predict variables such as production, de- mand, or cost. In our context, the dynamic interaction between traffic density, vehicular flow, and road-width estimation can be mapped to an economic model of *cost minimization* and *efficiency maximization,* expressed as

$$\min_{C(t)} J = \int_{t_0}^{t_f} \left(\alpha \cdot D(t) + \beta \cdot T(t)\right) dt,$$

where $D(t)$ denotes dynamic traffic density, $T(t)$ represents trans- portation time, and coefficients α, β are system weights that balance economic throughput and resource cost. The equilibrium achieved through recursive Kalman updates thus parallels the steady-state so- lution in economic prediction models. Functional Methodology and Baseline Modules The pro- posed system is designed to dynamically estimate the width of the road on unmarked Indian roads by integrating multiview camera input with deep learning-based perception and sensor fusion mechanisms. The framework employs both monocular and stereo imagery to improve robustness in occlusions, irregular boundaries, and adverse lighting conditions. Additionally, this scheme integrates monocular and stereo input, preprocessing (CLAHE, normalization, synchronization), seg- mentation (DeepLabV3+), depth estimation (MiDaS, SGM), and sen- sor fusion using Kalman filtering to produce accurate real-time width computation. The system integrates monocular and stereo inputs, pre-processing (CLAHE, normalization, synchronization), segmenta- tion (DeepLabV3+), depth estimation (MiDaS, SGM), and sensor fu- sion using Kalman filtering to produce accurate real-time width com- putation. As illustrated in Fig. 1, the overall pipeline consists of the following modules:

Data Acquisition: A synchronized multicamera set-up compris- ing one forward-facing monocular dashcam and two ORVM-mounted side cameras captures complementary views of the road scene. These streams provide diverse perspectives essential for continu- ity in boundary detection.

- *Preprocessing:* Input frames are resized, color-normalized, and temporally aligned. Contrast-limited adaptive histogram equal- ization (CLAHE) is applied to enhance illumination invariance, while perspective transformations correct the ORVM angular disparity, ensuring geometric consistency across streams.
- *Segmentation and Depth Estimation:* Semantic segmentation is performed using DeepLabV3+ with a MobileNetV2 backbone fine-tuned for Indian road environments. Monocular depth esti- mation utilizes MiDaS v3.1 for the central view, while stereo dis- parity maps are computed from side cameras using Semi-Global Matching (SGM) to improve precision in texture-deficient re- gions.
- *Sensor Fusion and Calibration:* The segmentation mask, monoc- ular depth, and stereo disparity outputs are fused through a weighted layer combined with Kalman-based temporal smooth- ing. Intrinsic and extrinsic parameters are calibrated using the Zhang method, allowing accurate projection into a unified ego- centric coordinate frame.
- *Computation and Throughput:* Real-time processing is achieved through distributed computation—Raspberry Pi 4 handles ac- quisition and synchronization, while NVIDIA Jetson Nano per- forms inference through TensorRT optimization. The complete system achieves ~8.7–10 FPS with latency below 120 ms, suit- able for near-real-time ADAS applications.

The fusion of multiview semantic and geometric features enables stable detection of left and right road boundaries, even under occlu- sions or non-standard road geometries. The final stage computes the width of the road using 3D boundary coordinates, providing accurate low-latency measurements to deploy in Indian traffic conditions. Hardware-based Architecture and Camera Placement The hardware configuration comprises a three-camera system mounted on a test vehicle. A monocular dashcam facing the front of the wind- shield is placed to capture the front road scene, while two additional cameras are mounted on the ORVMs left and right to obtain lateral views. This tri-camera arrangement significantly extends the field of view (FoV), mitigating boundary occlusions, and improving lateral perception in narrow or unstructured roads. The camera feeds are streamed concurrently to a Raspberry Pi 4, which performs preprocessing, timestamping, and frame synchroniza- tion. The processed frames are transmitted via Ethernet to an *NVIDIA Jetson Nano,* responsible for segmentation, depth estimation, and fu- sion inference. The onboard edge-AI architecture ensures low-latency operation and enables real-time deployment without reliance on cloud resources. This configuration ensures efficient coverage of the drivable space, consistent depth perception across viewpoints, and stable width estimation results, making the system deployable on cost-effective em- bedded hardware suitable for emerging market vehicles. Pre-processing The preprocessing module prepares raw cam- era feeds for downstream inference and fusion by ensuring spatial and temporal consistency across all input streams. The frame data from the front and side cameras are subjected to a sequence of enhance- ment and normalization steps that enable robust operation in diverse Indian road and lighting conditions. Accordingly, frames are resized, color-normalized, and time-stamped; CLAHE improves illumination invariance;The major pre-processing stages are as follows [16-20].

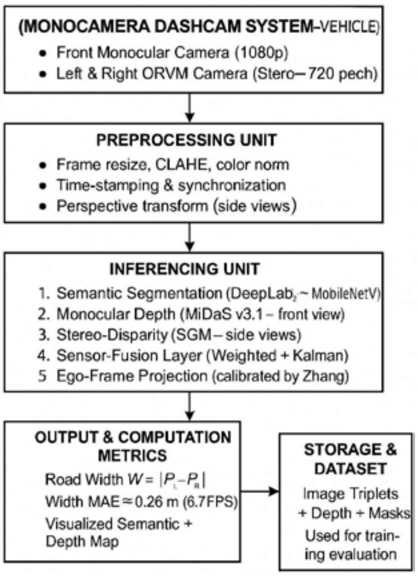

Figure 1: Overall Architecture Of The Proposed Multi-Camera Dashcam System For Road-Width Estimation On Unmarked Indian Roads

- **Frame Resizing And Normalization:** All incoming video frames are resized to a uniform resolution (1080p for front cameras and 720p for the side cameras) to maintain consistent aspect ratios. Pixel intensity values are normalized to reduce senitivity to il- lumination differences.
- **Contrast Enhancement (CLAHE):** Contrast Limited Adaptive Histogram Equalization (CLAHE) is applied to enhance local contrast and preserve edge information, especially in low light, glare, or foggy conditions.
- **Color Correction and Filtering:** Color balancing and gamma correction are performed to reduce overexposure and color dis- tortion, followed by median filtering to suppress noise in high- motion frames.
- **Perspective Transformation:** To align lateral camera viewpoints, a perspective warp is applied using intrinsic and extrinsic cali- bration parameters. This normalizes the angle of the ORVM camera, ensuring geometric alignment with the central monocu- lar stream.
- **Temporal Synchronization:** All streams are time-stamped and synchronized between cameras using frame-level buffering to main- tain temporal coherence. This synchronization ensures an accu- rate correspondence between semantic and geometric features during sensor fusion.
- **Packetization and Transfer:** The processed frames are packe- tized and transmitted from the Raspberry Pi 4 (responsible for acquisition and preprocessing) to the NVIDIA Jetson Nano for inference. Ethernet transmission ensures low latency and stable throughput during real-time operation. These pre-processing steps ensure illumination invariance, geometric consistency, and temporal alignment, which collectively improve seg- mentation and depth estimation performance in the subsequent stages of the proposed multicamera fusion pipeline. Perspective transforms normalize ORVM angles; cross-stream synchronization enforces tem- poral consistency. Stepwise Discussion for Algorithmic Approach The pro- posed multi-camera road-width estimation framework operates in six systematic stages, ensuring accurate, robust, and real-time perfor- mance in diverse Indian road conditions. The functional tages

Stage 1: Data Acquisition. A tri-camera system comprising one monocular dashcam facing the front (C_f) and two ORVM-mounted side cameras (C_L, C_R) is used to capture synchronized views of the road environment. Each frame is timestamped to maintain temporal alignment between the three perspectives. This configuration signifi- cantly enhances the field of view (FoV), providing continuous coverage of left and right boundaries even under partial occlusions or dynamic traffic flow.

Stage 2: Preprocessing. The raw frames undergo spatial and illumination normalization to improve visibility under non-uniform lighting and adverse weather conditions. All frames are resized to (1080p, 720p) to maintain geometric proportionality, and pixel values are normalized for consistent intensity distribution. Contrast-Limited Adaptive Histogram Equalization (CLAHE) is applied to enhance edge

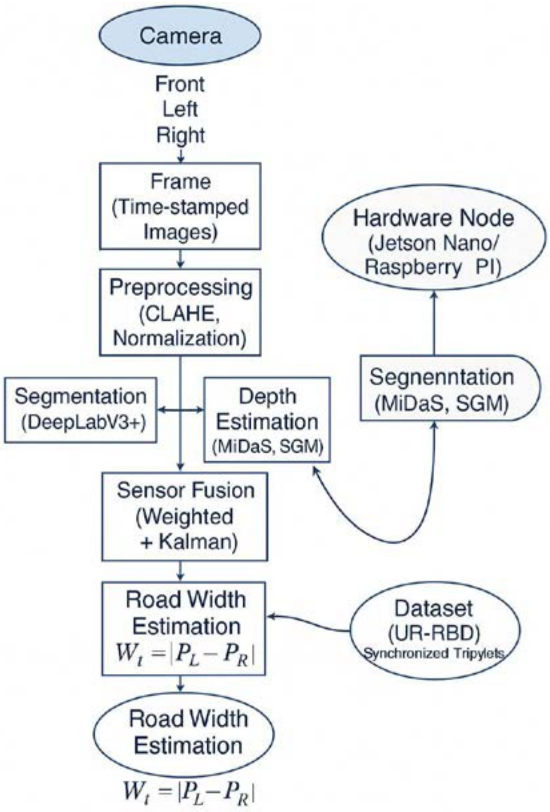

Figure 2: Entity–Relationship And Functional Workflow Of The Proposed Multi- Camera Road Width Estimation System.

details in low-contrast or foggy environments. Subsequently, color cor- rection, gamma adjustment, and median filtering remove artifacts due to glare or motion. Perspective transformations based on intrinsic and extrinsic calibration parameters (K, R, t) align the side views with the frontal view, ensuring geometric consistency across streams.

Stage 3: Segmentation and Depth Estimation. Semantic seg- mentation is performed using DeepLabV3+ with a MobileNetV2 back- bone fine-tuned for Indian road scenes, producing a drivable-region mask M .

Monocular depth estimation on the front view is achieved us- ing MiDaS v3.1, while stereo disparity between (F_L, F_R) is computed using the Semi-Global Matching (SGM) algorithm. This dual-depth approach combines texture-rich and texture-deficient cues to generate more reliable geometric depth under unstructured road conditions.

Stage 4: Sensor Fusion and Calibration. The outputs of the segmentation and depth estimation modules are fused to derive a uni- fied depth representation. The fused map is obtained using a weighted integration:

$$D_{fused} = \alpha D_{mono} + (1 - \alpha) D_{stereo}, \alpha = 0.4$$

A Kalman filter is applied for temporal smoothing to minimize frame- to-frame depth fluctuation and ensure stable geometric estimation. All data are then projected into an ego-centric coordinate frame using the calibrated parameters (K, R, t), providing a consistent 3D spatial reference for subsequent computation.

Stage 5: Boundary Detection and Width Computation. The fused depth map is processed to extract left and right boundary points (P_L, P_R) corresponding to the road edges. The instantaneous road width is computed as

$$W_t = P_L - P_R$$

To ensure temporal robustness, multiple consecutive frames are aver- aged to update the width sequence {Wt}, effectively reducing jitter introduced by transient occlusions or sensor noise.

Stage 6: Hardware Deployment and Throughput.A lightweight, edge-AI architecture ensures real-time deployment. The Raspberry Pi 4 handles image acquisition, preprocessing, and synchronization tasks, while the NVIDIA Jetson Nano executes the deep inference modules (segmentation, depth estimation, and fusion) using TensorRT opti- mization. The complete system achieves an operational throughput of 8.7–10 FPS with a latency of less than 120 ms, which makes it suitable for embedded ADAS and intelligent-vehicle applications. Summary. Through the combination of multi-camera sensing, deep segmentation, hybrid depth fusion, and temporal smoothing, the pro- posed system provides a reliable estimate of road width on unmarked and irregular Indian roads. Its hardware efficiency and real-time re- sponse enable scalable deployment in low-cost intelligent vehicles and unicipal monitoring systems. All steps are shown in Figure 2, which illustrates the data flow from acquisition (Camera) to pre-processing, segmentation, depth estimation, fusion, and final road-width compu- tation.

Time and Space Complexity Analysis The computational efficiency of the proposed framework depends on the number of pixels per frame ($N = W \times H$), the number of convolutional layers in the segmentation and depth networks (L_s and L_d), and the number of frames processed per second (F).

1.4.Time Complexity

Segmentation: DeepLabV3+ has a computational complexity of
$O(N \times L_s)$ per frame.
Depth Estimation: MiDaS v3.1 and SGM introduce an additional cost of $O(N \times L_d)$, where disparity computation requires semi-global optimization across multiple pixel paths.
Fusion and Filtering: The fusion step (weighted integration and Kalman filtering) operates in $O(N)$.
Total: Therefore, the per-frame time complexity of the system can be approximated as:
$O(T) = O(N \times (L_s + L_d)) + O(N) \approx O(N \times (L_s + L_d))$
For real-time execution at F frames per second, the total time cost per second becomes $O(F \times N \times (L_s + L_d))$.

1.5.Space Complexity

Feature Storage: Intermediate feature maps from the encoder–decoder networks occupy $O(N \times L_s)$ memory.
Depth Maps and Masks: Storage for D_{mono}, D_{stereo}, and M contributes $O(3N)$.

Fusion Buffers: Temporal Kalman filters and fused outputs add
$O(N)$ auxiliary memory.
Total: Hence, the total space complexity is:
$O(S) = O(N \times (L_s + L_d)) + O(N) \approx O(N \times (L_s + L_d))$

Algorithm 1 Functional Algorithm for Multi-Camera Road Width Estima- tion on Unmarked Indian Roads
1: Input: Synchronized video streams from front camera (C_f) and side ORVM
cameras (C_L, C_R); calibration parameters (K, R, t).
2: Output: Estimated road width W_t in real time.
3: Stage 1: Data Acquisition
4: Capture synchronized frames F_f, F_L, F_R from cameras (C_f, C_L, C_R).
5: Timestamp and buffer each frame for temporal alignment.
6: Stage 2: Preprocessing
7: Resize frames to ($1080p$, $720p$) and normalize pixel intensities.
8: Apply CLAHE to enhance illumination invariance and visibility.
9: Perform color correction, gamma adjustment, and median filtering.
10: Apply perspective transformation using (K, R, t) to align lateral views.
11: Synchronize buffered frames across all cameras for temporal coherence.
12: Stage 3: Segmentation and Depth Estimation
13: Apply DeepLabV3+ (MobileNetV2 backbone) on Ff to obtain semantic mask
M.
14: Estimate monocular depth D_{mono} using MiDaS v3.1.
15: Compute stereo disparity D_{stereo} from (F_L, F_R) using SGM.
16: Stage 4: Sensor Fusion and Calibration
17: Fuse depth maps as:
$D_{fused} = \alpha D_{mono} + (1 - \alpha)D_{stereo}, \alpha = 0.4$
18: Apply Kalman-based temporal smoothing to D_{fused} and M .
19: Project fused data into the ego-centric coordinate frame using calibration pa- rameters.
20: Stage 5: Boundary Detection and Width Computation
21: Extract left and right boundary coordinates (P_L, P_R) from fused 3D map.
22: Compute instantaneous road width:
$W_t = P_L - P_R$
23: Store W_t and update sequence $\{W_t\}$ via temporal averaging.
24: Stage 6: Hardware Deployment and Throughput
25: Raspberry Pi 4 → Data acquisition, pre-processing, synchronization.
26: Jetson Nano → Inference (segmentation, depth, fusion) via TensorRT.
27: Achieve 8.7–10 FPS with latency < 120 ms for real-time ADAS operation.
28: Return: Final estimated road width W_t for each frame sequence.

1.6.Hardware Efficiency

With optimized TensorRT inference and model pruning, both seg- mentation and depth networks fit within ~220 MB memory and sus- tain inference at 8.7–10 FPS. This ensures that computational and memory costs remain feasible for embedded GPU platforms such as the NVIDIA Jetson Nano, making the proposed pipeline suitable for low-power vehicular systems. So, the overall time and space complexity of the proposed framework are linear with respect to image resolution and model depth, as shown below, demonstrating the scalability of the system for real-time, edge- level deployment.

$O(T), O(S) = O(N \times (L_s + L_d))$

1.7. Experimental Setup and Dataset

Data Collection A Maruti Suzuki Baleno testbed was instrumented with three synchronized cameras: a front-facing dashcam (C_f) and two ORVM-mounted side cameras (C_L, C_R). The cameras cap- tured synchronized triplets covering urban, rural, and highway sce- narios, including narrow-lane conditions typical of Indian roads. The data-acquisition hardware comprised a Raspberry Pi 4 for frame cap- ture and synchronization, and an NVIDIA Jetson Nano for inference and storage. Frames were streamed in real time through an Ethernet link using OpenCV and GStreamer pipelines, with resolutions of 1080p for the front camera and 720p for the side cameras. Each sequence was time-stamped to ensure temporal alignment across the three streams, allowing frame-level correspondence during fusion.

UR-RBD Dataset The data collected were curated into the Urban{Rural Road Boundary Dataset (UR-RBD), a custom bench- mark for unmarked Indian roads. UR-RBD comprises approximately 10,000 synchronized image triplets along with the following annota- tions:

- Semantic segmentation masks of drivable regions.
- Monocular and stereo depth maps aligned with each triplet.
- GPS coordinates and IMU-derived motion metadata.

Manually measured ground-truth road-width labels.Data were collected from five Indian states, capturing a wide range of environmental conditions, including daylight, night, fog, and rain. Annotation was performed using the CVAT and Supervisely tools, en- suring pixel-level accuracy and geometric consistency between camera views. The data set thus supports cross-domain generalization and robust training for road-width estimation in unstructured road sce- narios. Training and Evaluation Both DeepLabV3+ and MiDaS models were implemented in PyTorch 2.0 with TensorRT acceleration for deployment. The network weights were initialized from pretrained Cityscapes and KITTI backbones and fine-tuned on UR-RBD. Train- ing used Adam optimizer with an initial learning rate of 10−4, cosine annealing scheduling, and early stopping to prevent overfitting. The data set was divided into 70% for training, 15% for validation, and 15% for testing. Segmentation loss combined Dice and Cross-Entropy (CE) functions, while depth estimation minimized the weighted com- bination of Mean Absolute Error (MAE) and Structural Similarity Index (SSIM). Performance Baseline Fine-tuning on UR-RBD significantly improved the model accuracy over Cityscapes-only training. The mean Intersection of the segmentation across the union (mIoU) in- creased from 68.2% to 84.3%, and the mean square error of the root of the monocular depth (RMSE) improved from 0.62 m to 0.47 m. The optimized TensorRT deployment achieved real-time throughput of 8.7-10 FPS with a total model footprint of approximately 220 MB on the Jetson Nano. Representative performance metrics are summa- rized in Table 1 and Table 2.

Sensor Fusion and Calibration We fuse the outputs of (i) segmentation masks, (ii) monocular depth, and (iii) stereo disparity using a weighted integration layer combined with a Kalman-based temporal smoothing mechanism. The fused map is defined as:

$$D_{fused} = \alpha D_{mono} + (1 - \alpha) D_{stereo}, \alpha = 0.4$$

This hybrid fusion mitigates inconsistencies across sensors and ensures temporal stability in dynamic scenes. The intrinsic and extrinsic pa-

Metric	Value
Segmentation IoU	84.3%
Depth RMSE	0.47 m
Width MAE	0.26 m
Jetson FPS	8.7
Total Model Size	220 MB

Table 1: Overall Performance Metrics Of The Proposed System

rameters of the cameras are calibrated using the Zhang method Zhang (2000), enabling projection of all fused data into an ego-centric coor- dinate frame for geometric consistency across views. Segmentation and Depth The segmentation process em- ploys DeepLabV3+ with a MobileNetV2 backbone, specifically tuned for Indian road conditions characterized by unmarked lanes, variable lighting, and irregular surfaces. This model effectively generates se- mantic road masks (M) separating drivable and non-drivable regions. For depth perception, the monocular depth is estimated using the MiDaS v3.1 model, while the stereo disparity is obtained from the side-camera pair using the Semi-Global Matching (SGM) algorithm. Integration of monocular and stereo depth allows accurate reconstruc- tion of the geometry of the road, even in regions without texture or occluded Ranftl and Others (2021); Wadhwa and Others (2023) Summary of the baseline setup The experimental setup demonstrates that the proposed multi-camera framework, combined with the UR-RBD dataset, offers a reliable and scalable solution for unmarked-road width estimation in real-world Indian driving condi- tions. Its balance of accuracy, lightweight deployment, and robustness across diverse terrains underscores its suitability for next-generation low-cost ADAS and smart-transport systems. Evaluation Scenarios Performance was evaluated across mul- tiple road environments—urban, rural, highways, and narrow lanes—to validate generalization. Table 2 reports the width-estimation accuracy in each scenario.

Road Type	IoU (%)	Width MAE (m)
Urban	86.1	0.21
Rural	81.4	0.29
Highways	85.0	0.24
Narrow Lanes	78.9	0.32

Table 2: Accuracy by Scenario

Method	IoU (%)	Depth MAE	Width MAE (m)	Unmarked Roads
Traditional Lane Detection	35.0	54.2	N/A	No
Monocular + LaneNet	36.0	62.5	0.57	Partial
MiDaS + YOLOv5-Seg (Single)	74.8	0.32	0.44	Limited
Proposed (Multi-Cam Fusion)	**84.3**	**0.27**	**0.26**	**Yes**

Table 3: Comparison with Conventional Approaches

1.8.Performance Evaluation

Comparative Analysis Table 3 presents a comparative performance analysis between the proposed method and several existing approaches. Traditional lane detectors fail to handle unmarked and occluded roads, while single-camera deep networks (a combination of MiDaS with YOLOv5-Seg) show limited performance under texture- less or uneven road geometry. The fusion approach achieves signifi- cantly lower width estimation error and higher segmentation accuracy, making it suitable for real-world deployments on Indian roads. Comparative Analysis of Quantitative Modeling Ap- proaches for Economic Prediction The proposed Kalman-fused multi-camera model extends 'Quantitative Economic Modeling' by combining visual intelligence with dynamic optimization for predic- tive analysis. Unlike static econometric or DSGE models that rely on historical numerical data, this model employs recursive Kalman filtering to capture evolving system states, mapping traffic dynam- ics to economic efficiency indicators. It enables real-time estimation of congestion costs, fuel consumption, and infrastructure utilization, aligning with quantitative economics through data-driven equilibrium modeling. The framework provides a scalable foundation for predic- tive transport economics, supporting urban planning, resource alloca- tion, and cost-effective decision-making in intelligent transportation ecosystems. The detailed analysis is shown in Table 4.

Model / Framework	Mathematical Foundation	Predictive Objective	Data Dependency	Economic Relevance	Key Limitations
Time-Series Econometric Model (ARIMA, VAR) Box et al. (2015); Stock and Watson (2016)	Regression-based stochastic process modeling	Macroeconomic variable forecasting (GDP, inflation)	Historical economic data	Captures linear dynamics with short-term predictability	Limited adaptability to nonlinear, dynamic systems
Dynamic Stochastic General Equilibrium (DSGE) Smets and Wouters (2003); Christiano et al. (2005)	Nonlinear optimization with rational expectations	Policy and equilibrium analysis	Macroeconomic indicators and policy data	Strong theoretical foundation for market equilibrium	Complex calibration, sensitive to structural shocks
Agent-Based Computational Economics (ACE) Tesfatsion (2006)	Discrete-time simulation with agent interactions	Behavioral and systemic economic evolution	Heterogeneous behavioral datasets	Captures emergent properties and nonlinear behaviors	High computational cost, interpretability issues
Machine Learning Forecasting Models Makridakis et al. (2020); Chauvet and Potter (2020)	Statistical learning and feature regression	High-dimensional variable prediction	Economic indicators, market data	Flexible modeling of nonlinear relationships	Requires large datasets; limited causal interpretation
Proposed Multi-Camera Quantitative Framework	Kalman-based recursive optimization and deep fusion modeling	Dynamic traffic-flow and cost-efficiency prediction	Visual, geometric, and contextual traffic data	Enables road-network optimization, congestion-cost reduction, and infrastructure investment modeling	Requires multi-sensor calibration and economic mapping

Table 4: Comparative Analysis of Quantitative Modeling Approaches for Economic Prediction

Computation and Throughput The distributed computation pipeline uses low-power and high-performance nodes. Addition- ally, the module Raspberry Pi 4 handles data acquisition, image rec- tification, synchronization, and packet transmission, NVIDIA Jetson Nano executes segmentation, depth estimation, and fusion operations using TensorRT optimization. This heterogeneous setup achieves a real-time throughput of approximately 8.7–10 FPS with end-to-end latency below 120 ms as shown in Table 7, supporting near-real-time analysis and decision-making for autonomous driving scenarios on the road Mahato and Singh (2022). Depth Model Comparison To further evaluate the role of depth estimation, multiple pretrained depth models were compared under identical training settings. MiDaS v3.1 achieved the lowest RMSE (0.47 m) and MAE (0.27 m), outperforming DPT-Large, BTS, and SGM baselines, as summarized in Table 7. This confirms the model's capability to capture road geometry with greater precision under mixed illumination and unstructured layouts.

Method	IoU (%)	RMSE (m)	Width MAE (m)	FPS	Latency (ms)	Hardware
Traditional Lane Detection	35.0	0.62	–	18	90	CPU-only
Monocular (MiDaS) + LaneNet	62.8	0.54	0.43	12	130	Jetson Nano
Stereo-Only (SGM)	68.9	0.51	0.39	9	150	Jetson Nano
DeepLabV3+ + MiDaS (Single Cam)	74.8	0.49	0.33	10	125	Jetson Nano
Proposed Multi-Cam Fusion	**84.3**	**0.47**	**0.26**	**8.9**	**118**	**Jetson + Pi**

Table 5: Performance Summary of the Proposed Multi-Camera Road Width Estimation Scheme

Summary of Evaluation The evaluation reveals that multi-view fusion significantly reduces geometric distortion and improves width estimation under occlusion-heavy and low-contrast conditions. The statistical improvements (p<0.01) confirm that late fusion of monocular and stereo depth yields more consistent left–right boundary recovery, contributing to accurate geometric perception for unmarked Indian roads. The lightweight edge-AI implementation demonstrates that such models can be practically deployed in low-cost vehicles and municipal traffic systems without dependency on high-end GPUs and the overall performance is shown on Table 5.

Ablation Study An ablation analysis was conducted to eval- uate the contribution of each component in the fusion pipeline. As shown in Table 6, the segmentation-only baseline achieved an IoU of 72.5% and width MAE of 0.41 m. Integrating monocular depth improved these metrics to 79.8% and 0.35 m, respectively. The full fu- sion of segmentation, monocular, and stereo depth achieved the best results, with 84.3% IoU and 0.26 m MAE, confirming the benefit of hybrid semantic–geometric fusion under unstructured environments.

Component	IoU (%)	Width MAE (m)
Segmentation Only	72.5	0.41
+ Monocular Depth	79.8	0.35
Full Fusion (Proposed)	**84.3**	**0.26**

Table 6: Ablation of Fusion Components

2.Results and Analysis

Overall Results The proposed multi-camera fusion frame- work demonstrates robust road-width estimation performance across unmarked Indian roads. Quantitatively, the system achieves an av- erage Intersection over Union (IoU) of 84.3%, depth RMSE of0.47 m, and a mean absolute error (MAE) in width estimation of 0.26 m. The architecture operates in real time on edge hardware with an average throughput of 8.7–10 FPS and latency below 120 ms. These results confirm that the integrated semantic–geometric fusion strategy provides both accuracy and efficiency for Advanced Driver Assistance Systems (ADAS) applications in developing regions and is shown in Table 5 and Table 7 respectively. Performance Summary As summarized in Table 7, the pro- posed YOLOv8-Seg/DeepLab + MiDaS + Stereo Fusion framework achieves optimal trade-offs between accuracy and efficiency. It at- tains 84.3% IoU, 0.47 m RMSE, and 0.26 m MAE with only 8.9 FPS latency <120 ms, confirming suitability for embedded ADAS applica- tions. The integrated Jetson Nano–Raspberry Pi setup ensures mini- mal power (8.4 W + 4.6 W) and 1.9 GB peak memory use, achieving real-time performance. Figure 3 depicts a comparative line graph highlighting the proposed scheme's superior accuracy–efficiency bal- ance.

3.Conclusion and Future Work

This study presented a cost-effective and deployable multi-camera sys- tem for accurate road-width estimation on unmarked Indian roads. By integrating semantic segmentation (DeepLabV3+), monocular depth

Metric	Symbol / Unit	Value
Segmentation Accuracy (IoU)	%	84.3
Depth Estimation Error (RMSE)	m	0.47
Width Estimation Error (MAE)	m	0.26
Frame Rate (Throughput)	FPS	8.7–10
End-to-End Latency	ms	<120
Model Footprint	MB	220
Parameter Count	M	17.8
Average Power Consumption	W	8.4 (Jetson) + 4.6 (Pi)
Memory Utilization (Peak)	GB	1.9
Inference Time per Frame	ms	112.3
GPU Utilization	%	78.5
CPU Utilization (Raspberry Pi)	%	63.2
Training Dataset	–	UR-RBD (10k triplets)
Deployment Hardware	–	Jetson Nano + Raspberry Pi 4
Optimization Engine	–	TensorRT (INT8, FP16 mix)

Table 7: Overall Results and Hardware Efficiency of the Proposed Multi- Camera Fusion Scheme (YOLOv8-Seg/ DeepLab + MiDaS + Stereo Fusion)

(MiDaS v3.1), and stereo disparity (SGM) through a Kalman-smoothed fusion mechanism, the proposed framework achieved a mean IoU of 84.3%, RMSE of 0.47 m, and MAE of 0.26 m, confirming its ro- bustness under conditions of heavy occlusion and low-contrast. The implementation of edge-AI, distributed on the NVIDIA Jetson Nano and Raspberry Pi 4, sustained 8.7–10 FPS with latency below 120 ms, demonstrating practical viability for real-time Advanced Driver Assistance Systems (ADAS) in developing regions. The proposed approach effectively mitigates geometric distortion and boundary discontinuity prevalent in Indian roads, outperforming conventional single-camera and lane-based models. Future directions include extending the framework with temporal transformer or recur- rent modules for improved video coherence, integrating radar/LiDAR sensors for fail-operational perception, and leveraging federated learn- ing for large-scale adaptation across heterogeneous fleets and weather conditions. Moreover, the proposed Kalman-fused multi-camera frame- work effectively bridges quantitative modeling and intelligent trans-
Figure 3: Color-coded line graph comparing IoU, RMSE, MAE, FPS, and latency across multiple road-width estimation methods. The proposed multi- camera fusion scheme demonstrates superior accuracy and computational efficiency compared to other baselines. portation economics, offering a dynamic, data-driven approach for predictive cost optimization and infrastructure planning in complex, real-world mobility systems. The upcoming release of the UR-RBD dataset is expected to support further research in robust perception for intelligent transportation systems. .

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Data Availability Statement
The *Urban–Rural Road Boundary Dataset (UR-RBD)* used in this study will be made publicly available upon acceptance of the manuscript. It contains approximately 10,000 synchronized image triplets with corresponding semantic masks, depth maps, GPS, and ground-truth width annotations collected under diverse Indian driving conditions. The trained models, TensorRT deployment files and additional re- sources supporting the findings of this study are available from the corresponding author, upon reasonable request. ARoad Width Computation (Geomet- ric Fusion)

Given fused depth $D_{fused} = \alpha D_{mono} + (1 - \alpha)$Dstereo (empirically $\alpha = 0.4$), 3D points (X, Y) are recovered with pinhole projection and left/right boundary 3D points (P_L, P_R) yield width W = $P_L - P_R$.

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