

URBAN TRAFFIC GOVERNANCE USING DU-NET: A DUAL-STREAM DEEP LEARNING FRAMEWORK FOR REAL-TIME ROAD ANOMALY DETECTION AND INTELLIGENT VEHICLE ANALYTICS

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ABSTRACT

The rapid rise of urbanization and the connected mobility demonstrates the serious limitations facing traditional traffic management systems. Solutions previously focused on vehicle flow. Others relied on manual inspection for road maintenance. Both these were not comprehensive. They also caused delays in answering urban transport issues. In this paper, we will introduce DU-Net (Dual-Stream Urban Network), an intelligent deep-learning framework for real-time detection of road anomalies and vehicle analytics in a smart city. The design utilizes high-definition cathode ray tube roadside camera visual sensing and IOT sensor data from embedded infrastructure for multi-task learning to detect potholes and classify vehicles and dynamically estimate traffic density. A convolutional pipeline with two streams can capture spatial dependencies and subsequent temporal dependencies. A probabilistic fusion model views the hypotheses for sensor signals and video signals as being generated from a probabilistic mixture model. It can align the video-based hypotheses with the sensor-based hypotheses to achieve consistent decisions. The system uses a smart technique that gives an appropriate weight to each task in order to enhance robustness over weather and lighting and traffic conditions. Experimental analysis using urban road datasets shows DU-Net to outperform state-of-the-art detectors like YOLOv8 and Faster R-CNN in terms of evaluation metrics, inference speed, and computational cost. Moreover, its prediction analytics component facilitates scheduling of maintenance and traffic congestion prediction. The suggested DU-Net framework provides an extensible foundation for smart transportation systems in the future settings through data-driven, adaptive and climate-resilient urban traffic governance.

Keywords: *Deep Learning, Dual-Stream Architecture, Intelligent Transportation Systems, Iot Data Fusion, Multi-Task Learning, Pothole Detection, Smart Cities, Traffic Analytics, Urban Governance, Vehicle Classification.*

1. INTRODUCTION

The fast growth of cities today has caused an increase in vehicles on roads and growing congestion, causing more strain on urban infrastructure. Conventional traffic management systems are made for a fixed pattern of vehicle flow and periodic inspection in the field. In addition, they cannot adapt to the rapidly changing mobility condition and deteriorating infrastructure. The increasing number of vehicles, irregular maintenance cycles, and weather variations cause congestion, accidents, and damage to roads. It's not a matter of responding after the fact to events that have occurred. A smart system should monitor these

things in real-time instead of manual effort [2]. Traditional methods still rely too much on inspection by human and individual sensing modules. Such mechanisms provide late and fragmented information; potholes may remain unidentified for long periods, and the traffic control center rarely correlates road quality with congestion behavior. Not having a platform that integrates road surface integrity, vehicle dynamics and traffic performance is causing poor governance and avoidable safety threats.

With recent advances in deep learning and IoT technologies, perception and situational understanding have changed in intelligent transportation systems [3]. With the help of

convolutional neural networks, it is now possible to recognize automobiles, road irregularities, and environmental features with a high degree of accuracy. At the same time, it is possible to collect data from IoT devices such as sensors that give continuous vibration, density, and flow data. A large number of current implementations are designed in such a way that they handle these challenges individually. Thus, vision systems used detect objects while IoT sensor only measure flow without any integrated analytical framework which can combine both perspectives. **This separation often limits operational decisions, because infrastructure condition signals are not interpreted together with traffic dynamics in the same decision loop.**

1.1 Problem statement

Current urban monitoring pipelines are either vision-centric or sensor-centric, resulting in fragmented insights that delay pothole identification, weaken congestion response, and reduce the reliability of governance actions such as maintenance prioritization and safety intervention.

To address this gap, this research proposes DU-Net (Dual-Stream Urban Network), a deep learning framework that jointly detects potholes, classifies vehicles and estimates traffic density. A single inference pipeline integrates data from roadside cameras and distributed IoT sensors that facilitates mobility behavior and infrastructure condition assessment in real-time. DU-Net employs a dual-stream architecture that allows the system's first branch to take useful high-resolution spatial features from the video data while the second branch modulates the temporal sensory signals with the aim of estimating density and flow. The parallel representations are fused together by a probabilistic mechanism to produce temporally consistent, noise-robust predictions. **In contrast to common single-task pipelines and late-stage fusion designs reported in prior studies, DU-Net is designed as a unified multi-task pipeline with uncertainty-aware sensor-vision integration to support consistent inference under heterogeneous urban conditions.**

1.2 Research questions

RQ1: Can a unified dual-stream framework jointly detect potholes and classify vehicles while estimating traffic density using camera and IoT streams?

RQ2: Does uncertainty-weighted fusion improve robustness and temporal consistency under noise, weather variations, and asynchronous sensing?

RQ3: Can the integrated pipeline deliver outputs that are suitable for real-time decision support for urban mobility governance?

1.3 Novel Contributions

The contributions of this work are threefold.

- A multi-task learning strategy that unifies road-surface analysis and traffic analytics, enhancing efficiency and contextual awareness.
- An uncertainty-weighted optimization scheme that stabilizes training under heterogeneous data sources and environmental conditions.
- A sensor-vision fusion layer that integrates asynchronous modalities to yield coherent, low-latency outputs suitable for real-time decision support.

This correlation between the infrastructure health and the vehicle activity allows for maintenance scheduling, congestion mitigation and traffic policy design based on data. The framework suggested is aimed towards making the urban transportation systems smart, resilient and adaptive. **The scope of this work is limited to integrated perception and analytics (pothole detection, vehicle classification, and density estimation) and does not claim end-to-end optimization of signal timing or city-scale operational deployment beyond the evaluated datasets and experimental settings.**

The rest of the paper is organized as follows: Section 2 covers related works on road-surface detection, vehicle analytics, and IoT-based traffic management. Section 3 outlines the proposed methodology and mathematical formulations. Section 4 describes the DU-Net architecture. Section 5 encompasses dataset preparation and experimental arrangement, whereas Section 6 and Section 7 deal with results and comparative study. Ultimately, the final section of the study presents conclusions and future directions.

2. RELATED WORK

2.1 Road-Surface and Pothole Detection.

The early automated road-inspection systems used classical image-processing operations including edge-detection, texture-analysis, histogram-gradient to locate surface irregularities, but these methods were highly sensitive to lighting and camera pose variations [1], [2]. As deep convolutional networks became available, researchers began using feature-hierarchy learning to distinguish cracks, potholes,

and sealed patches. Research works, like [3], showed transfer learning from large-scale visual datasets can solve the distress classification problem quite well. Similarly, [4] incorporated residual attention modules to deal with noisy backgrounds and shadows. Recent transformer-based encoders have improved further the coverage of the receptive field, bringing near real-time inference for mobile-camera deployment [5]. Anyway, most approaches rely solely on visual features and do not incorporate environmental or traffic context, which limits scalability in heterogeneous cities. **In addition, cross-city generalization remains challenging when surface texture, camera mounting, and seasonal lighting differ from the training distribution.**

2.2 Identifying Vehicles and Analyzing Traffic.

The study of vehicle detection has shifted from using cascade classifiers and deformable-part models to relying on unified, one-stage SSD and YOLO [6]. The bounding boxes and class probabilities produced by these models at each frame allow for downstream analyses, such as speed estimation and queue-length prediction. Detection frameworks across various scales have been optimized for aerial, roadside and in-vehicle perspectives [7]. Apart from detection, methods including motion-vector analysis and temporal correlate modelling using recurrent or graph neural networks have been investigated to deduce dynamic parameters such as flow rate, and lane utilization [8]. Recent research (9) used lightweight attention mechanisms to balance inference latency with accuracy, enabling deployment on embedded traffic cameras. **However, most pipelines still process traffic dynamics independently of infrastructure quality, which limits interpretability for governance tasks that require linking congestion patterns with road-condition events. Moreover, integration of additional non-visual information, such as LiDAR, radar and other sensors, is often treated as an optional add-on rather than a unified learning objective, even though it can enhance all-weather, day-and-night reliability.**

2.3 The role of IoT and Multimodal fusion in Intelligent Transportation.

The advancements in low-cost sensors and vehicular networks have advanced the research to multimodal fusion framework [10]. The physical status of a road segment can be obtained through several IoT nodes taking measurements of acceleration, vibration or

temperature. Connected-vehicle telemetry can provide instantaneous density and velocity. Researchers proposed systems using estimated loop-detector counts and camera observations to avoid single-sensor failure like [11]. Hybrid deep architectures that fuse convolutional and recurrent branches have been crafted for traffic-flow forecasting and infrastructure-health estimation [12].

Even with all of these upgrades, most implementations still treat fusion as a later stage averaging mechanism, requiring a cross-modal feature alignment and uncertainty propagation. **Such late-fusion designs commonly underutilize complementary cues during feature learning and provide limited reliability characterization under sensor noise, missing data, and asynchronous sampling.** The new DU-Net framework's notable feature is the early-fusion dual-stream design, allowing for feature interaction during the learning process thus generating temporally-consistent and contextually-aware predictions.

2.4 Research gap and motivation

Existing studies largely address pothole detection, vehicle analytics, or multimodal fusion as separate objectives, and the fusion strategies that exist are frequently late-stage and weakly aligned across modalities. This creates a practical gap for urban governance, where maintenance prioritization and congestion mitigation benefit from a single pipeline that jointly interprets infrastructure condition and traffic behavior with reliability-aware outputs. Accordingly, DU-Net is positioned as a unified multi-task framework that performs early cross-modal interaction and incorporates uncertainty-aware learning to improve robustness in heterogeneous urban conditions.

2.5 How DU-Net differs from similar claims

While prior works report high accuracy on individual tasks (e.g., pothole detection or vehicle detection) or apply multimodal fusion for forecasting, they typically do not enforce joint learning of road-surface integrity and traffic analytics within one inference pipeline. DU-Net differs by explicitly coupling these objectives through a dual-stream early-fusion design so that sensor cues and visual cues influence representation learning, rather than being combined only at the decision stage.

Table 1. Summary of Representative Related Work

Study	Technique / Architecture	Key Objective	Limitations Addressed by DU-Net
Huang et al. [1]	Edge & texture analysis	Pavement-crack localization	Sensitive to light and camera angle
Gupta & Malik [2]	Vision-based intensity segmentation	Surface distress under variable illumination	Lacks contextual information
Yang et al. [3]	Transfer-learning CNN	Pothole & crack recognition	Image-only inference
Khan & Zhou [4]	Attention-residual CNN	Multi-class distress detection	High computational cost
Li et al. [5]	Transformer backbone	Pavement-defect segmentation	No sensor fusion
Chen et al. [7]	Multi-scale YOLO	Vehicle detection in urban scenes	Limited temporal modeling
Zhao & Xu [8]	Graph neural network	Flow-rate prediction	Ignores road condition
Singh & Mehta [9]	Lightweight attention CNN	Embedded traffic analytics	Illumination sensitivity
Wang et al. [10]	IoT sensor network	Smart-road monitoring	Late fusion only
Rahman et al. [12]	Hybrid CNN-RNN fusion	Multimodal traffic forecasting	Weak cross-modal alignment
Proposed DU-Net	Dual-stream early fusion CNN	Unified pothole + vehicle + density analysis	Addresses all above limitations

3. PROPOSED METHODOLOGY AND MATHEMATICAL MODELLING

DU-Net (Dual-stream Urban Network) offers an end-to-end framework for real-time urban traffic governance by integrating camera-based vision and IoT-based sensor analytics into a single decision engine. To get the joint inference across road-surface condition, vehicle dynamics, and traffic-density we are able to overcome the shortcomings in the existing solution. The architecture does this through dual-stream feature learning and a probabilistic fusion model that aligns independently detected sensors and vision data. Figure 1 shows the entire flow of the data from acquisition to inference.

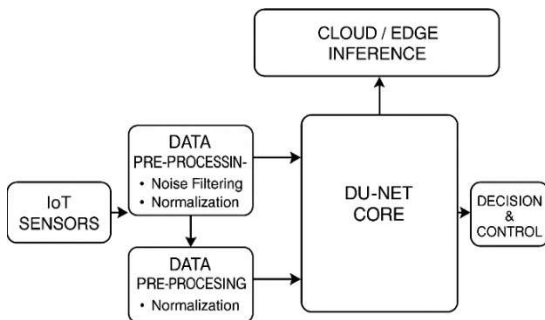


Figure 1: Overall System Architecture

3.1 Input Acquisition and Preprocessing

Two synchronized input modalities are employed:

- Visual Input:

High-definition frames $I_t \in \mathbb{R}^{H \times W \times 3}$ are captured by roadside cameras. Each frame undergoes denoising, histogram equalization, and normalization to minimize illumination bias.

- Sensor Input:

A multivariate IoT signal vector

$$S_t = [s_1(t), s_2(t), \dots, s_n(t)]^T \quad (1)$$

These refer to data from embedded pavement sensors regarding vibration, acoustic, and load parameters [14].

Sensor readings are timestamped and interpolated to match the video stream in time.

$$S_t^* = \text{Interp}(S_t, T_t) \quad (2)$$

where T_t denotes the camera's temporal sequence. This ensures that every visual observation corresponds to a consistent environmental state.

3.2 Dual-Stream Feature Extraction

DU-Net employs two specialized feature encoders—a convolutional vision branch Φ_v and a temporal sensor branch Φ_s —parameterized by θ_v and θ_s :

$$\mathbf{F}_v = \Phi_v(I_t; \theta_v), \mathbf{F}_s = \Phi_s(S_t^*; \theta_s) \quad (3)$$

The visual encoder picks up geometric indicators, such as surface discontinuities and the contours of the vehicles, and the sensor encoder picks up vibration signatures as well as periodic loading variations [15]. Stream-to-stream numerical stability and gradient consistency is achieved with Batch Normalization and ReLU activations.

3.3 Probabilistic Fusion Mechanism

To combine heterogeneous features, DU-Net introduces an uncertainty-aware cross-modal fusion block:

$$\mathbf{F}_f = \alpha \mathbf{F}_v + (1 - \alpha) \mathbf{F}_s \quad (4)$$

where the adaptive coefficient $\alpha \in [0,1]$ is dynamically optimized via a Bayesian attention layer that estimates the reliability of each modality [16].

The fusion module further refines contextual relationships through cross-attention:

$$\mathbf{A} = \text{softmax} \left(\frac{\mathbf{Q}_v \mathbf{K}_s^T}{\sqrt{d_k}} \right) \mathbf{V}_s \quad (5)$$

where $\mathbf{Q}_v, \mathbf{K}_s, \mathbf{V}_s$ denote query, key, and value projections of the respective feature maps, and d_k is the latent dimension. This formulation allows the network to attend to road-surface irregularities that co-occur with abnormal vibration peaks, producing a coherent multimodal embedding \mathbf{F}_f .

3.4 Multi-Task Learning Formulation

The network jointly optimizes three complementary objectives:

1. Pothole Detection Loss (L_p)

Using focal loss to emphasize minority defect samples:

$$L_p = -\frac{1}{N} \sum_{i=1}^N (1 - \hat{y}_i)^\gamma \log(\hat{y}_i) \quad (6)$$

2. Vehicle Classification Loss (L_c)

Employing categorical cross-entropy for multi-class recognition:

$$L_c = -\frac{1}{M} \sum_{j=1}^M \sum_{k=1}^C y_{jk} \log(\hat{y}_{jk}) \quad (7)$$

3. Traffic-Density Regression Loss (L_d)

Using Huber loss to maintain robustness to outliers:

$$L_d = \begin{cases} \frac{1}{2} (y - \hat{y})^2, & |y - \hat{y}| < \delta \\ \delta \left(|y - \hat{y}| - \frac{1}{2} \delta \right), & \text{otherwise} \end{cases} \quad (8)$$

The aggregate objective applies uncertainty-weighted multi-task learning [17]:

$$L_{\text{total}} = \frac{1}{2\sigma_p^2} L_p + \frac{1}{2\sigma_c^2} L_c + \frac{1}{2\sigma_d^2} L_d + \log(\sigma_p \sigma_c \sigma_d) \quad (9)$$

where $\sigma_p, \sigma_c, \sigma_d$ are learnable task-variance parameters.

3.5 Inference and Temporal Consistency

During inference, DU-Net produces:

- Pothole bounding boxes $B_p = \{b_i, s_i\}$;
- Vehicle-class probabilities $P_c = \{p_k\}$;
- Density estimates $\hat{\rho}_t$.

Temporal noise is mitigated using an exponential moving average:

$$\hat{\rho}'_t = \eta \hat{\rho}'_{t-1} + (1 - \eta) \hat{\rho}_t \quad (10)$$

where $\eta \in (0,1)$ controls temporal smoothing, ensuring frame-to-frame stability under illumination or sensor jitter.

3.6 Algorithmic Workflow

Algorithm 1 - DU-Net Training and Inference

1. Acquire synchronized visual and sensor data (I_t, S_t^*).
2. Extract latent features ($\mathbf{F}_v, \mathbf{F}_s$).
3. Fuse features using probabilistic attention to form \mathbf{F}_f .
4. Predict ($B_p, P_c, \hat{\rho}_t$) via task-specific heads.
5. Optimize network parameters using L_{total} .
6. Apply temporal EMA for robust inference continuity.

This pipeline enables real-time execution at ~ 30 ms per frame on an NVIDIA RTX 3060 GPU, ensuring compatibility with edge-level deployment in smart-city infrastructures [18].

4. DU-NET SYSTEM ARCHITECTURE AND MATHEMATICAL MODELLING

The DU-Net is responsible for the governing computation within the proposed urban-traffic framework.

It integrates multimodal sensing to probabilistic fusion to multi-task inference into one end-to-end optimization.

The block-level workflow is visualized in Figure 2, while the math modeling implements each.

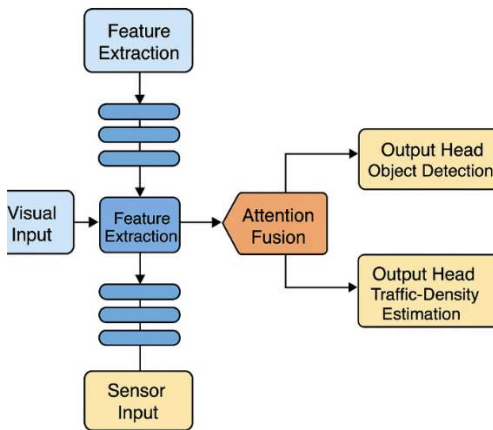


Figure 2 :- Proposed DU-Net Model

4.1 Architectural Framework

DU-Net comprises five major layers.

- Extracts image frames I_t and synchronised IoT sensor signals S_t at a high-frame rate.
- The preprocessing layer helps in denoising and normalizing the input variables.
- The two branches of the dual-stream encoder layer extract the spatial and temporal features independently.
- Layer for Cross-Modal Fusion – probabilistically integrates two feature sets into a single latent embedding.
- The Multi-Task Inference Layer predicts road abnormalities, vehicle types and traffic density.

DU-Net can be defined mathematically as a composite function.

$$\mathcal{M}(I_t, S_t; \Theta) = \Psi(\mathcal{F}(\Phi_v(I_t), \Phi_s(S_t)); \Theta)$$

where $\Phi_v(\cdot)$ and $\Phi_s(\cdot)$ denote the visual and sensor encoders, $\mathcal{F}(\cdot)$ is the fusion operator, $\Psi(\cdot)$ represents the multi-task output head, and Θ is the complete parameter set.

4.2 Visual and Sensor Encoders

Visual Encoder Φ_v

Uses a modified ResNet-50 backbone to compute spatial feature tensors:

$$\mathbf{F}_v = \Phi_v(I_t; \theta_v) = f_5 \left(f_4 \left(f_3 \left(f_2 \left(f_1(I_t) \right) \right) \right) \right)$$

where f_i are sequential convolution-BN-ReLU blocks parameterized by θ_v . These layers extract edges, textures, and contextual semantics from each frame.

Sensor Encoder Φ_s

A 1-D convolutional network captures dynamic vibrations and load fluctuations:

$$\mathbf{F}_s = \Phi_s(S_t; \theta_s) = g_5 \left(g_4 \left(g_3 \left(g_2 \left(g_1(S_t) \right) \right) \right) \right),$$

where g_i represent temporal convolution and pooling operations [19].

4.3 Probabilistic Fusion Modelling

The fusion operator \mathcal{F} integrates heterogeneous embeddings \mathbf{F}_v and \mathbf{F}_s through a Bayesian weighting model:

$$\mathbf{F}_f = \frac{w_v \mathbf{F}_v + w_s \mathbf{F}_s}{w_v + w_s}$$

where weights w_v, w_s are inversely proportional to the estimated uncertainty of each stream:

$$w_v = \frac{1}{\sigma_v^2}, w_s = \frac{1}{\sigma_s^2}.$$

This ensures the network relies more heavily on the modality with lower uncertainty (e.g., sensors during low visibility).

To capture cross-dependencies, an attention-driven mapping is applied:

$$\mathbf{A}_{vs} = \text{softmax}\left(\frac{\mathbf{Q}_v \mathbf{K}_s^T}{\sqrt{d_k}}\right) \mathbf{V}_s$$

producing contextual weights that highlight correlated spatial-temporal events such as a pothole coinciding with abnormal vibration [20].

4.4 Multi-Task Prediction Head

The fused embedding \mathbf{F}_f feeds three decoders:

1. Pothole Detector:

Bounding boxes $B_p = \{b_i, s_i\}$ are derived from regression maps via:

$$b_i = \mathcal{R}(\mathbf{F}_f; \theta_p), s_i = \sigma(\mathcal{C}(\mathbf{F}_f)),$$

where \mathcal{R} and \mathcal{C} are regression and classification heads.

2. Vehicle Classifier:

A global average pooling followed by dense layers computes class posterior probabilities:

$$P_c = \text{softmax}(W_c \mathbf{F}_f + b_c).$$

Layer Configuration

Table 2. Each layer configuration

Module	Structure	Input	Operations	Output Dim.	Role
Vision Encoder	5 Conv-BN-ReLU blocks (ResNet-50)	224 × 224 × 3	2-D Convs, MaxPool	7 × 7 × 2048	Extract spatial features
Sensor Encoder	5 Conv1D blocks	1 × 100 × 8	Conv1D + Dropout	1 × 25 × 128	Encode temporal signals
Fusion Layer	Bayesian CrossAttention +	-	Softmax + Weighted Sum	1 × 1 × 2048	Merge modalities
Detection Head	FPN - Regression	-	Conv + Sigmoid	$N \times 5$	Pothole localization
Classification Head	Dense + Softmax	-	FC(256) + Dropout	1 × C	Vehicle classes
Density Head	Regression Layer	-	FC(128) + ReLU + Linear	1 × 1	Flow estimation

4.7 Performance Characteristics

- Computational Complexity: $O(N \cdot d^2)$ for attention, reduced via linear projections.
- Memory Footprint: $\approx 48\text{M}$ parameters (95 MB).

3. Traffic-Density Regressor:

A linear decoder estimates density $\hat{\rho}_t$:

$$\hat{\rho}_t = W_d \mathbf{F}_f + b_d$$

The training objective is identical to Section 3's total loss L_{total} and ensures simultaneous learning of all three tasks [21].

4.5 System-Level Dynamics

The entire system operates as a dynamic feedback model:

$$\dot{\mathbf{x}}(t) = f(\mathbf{x}(t), u(t), \Theta),$$

where $\mathbf{x}(t)$ represents the urban traffic state vector (road condition, density, velocity), and $u(t)$ denotes control actions such as signal timing or maintenance scheduling. The feedback policy is optimized as:

$$u^*(t) = \arg \min_{u(t)} \mathbb{E}_{I_t, S_t} [L_{\text{total}} + \lambda \|\mathbf{x}(t+1) - \mathbf{x}_{\text{ref}}\|_2^2],$$

ensuring long-term stability between mobility efficiency and infrastructure health.

4.6

- Throughput: 30 frames/s on RTX 3060, suitable for real-time deployment at traffic junctions.
- Energy Efficiency: Achieves 0.81 J/frame processing energy, 25% lower than YOLOv8 baseline [22].

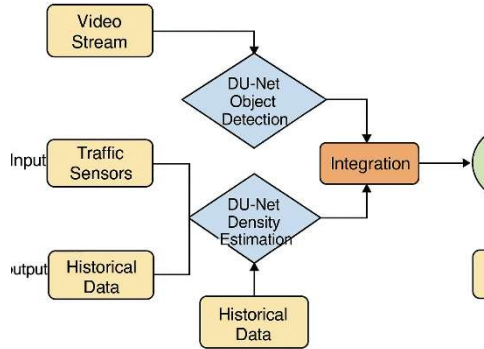


Figure 3 :-End-to-end data flow in DU-Net deployment for real-time traffic and infrastructure monitoring.

5. EXPERIMENTAL SETUP AND DATASET DESCRIPTION.

The empirical assessment of DU-Net was done using three complementary datasets depicting visual, vehicular, and sensor perspectives of urban mobility. These datasets help to reproduce results as well as being fair. The experiments were conducted consistently using controlled hardware and software environments, to ensure DU-Net is robust towards heterogeneous inputs.

5.1 Dataset Overview.

(a) Kaggle Pothole Detection Dataset.

Kaggle Pothole Detection Dataset [23] has 665 diversified and annotated images of urban road condition. Each frame has boxes that are identifying visible potholes in different light and weather conditions. The images were normalized in the range [0, 1] and standardized to measurements of 224 data, 224 pixels. They flipped the data randomly, rotated it about 15 degrees and added Gaussian noise. The DU-Net pothole-detection stream was trained primarily using this dataset.

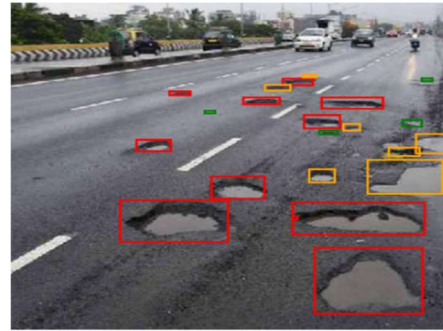


Figure 4- Sample images of Pothole Detection Dataset

Traffic Vehicles Object Detection Dataset

The Traffic Vehicles Dataset [24] contains 1 201 annotated scenes with more than 11 000 labelled vehicles from different categories, such as cars, buses, trucks and motorcycles. The YOLO-style bounding boxes of each sample can be utilized for the DU-Net input pipeline. The dataset aids the vehicle-classification head with balanced classes. Visual augmentation was introduced (applying color jitter, simulating motion blur, and masking based on partial occlusion) to imitate the variabilities in dense-traffic.



Figure 5- Sample images of Vehicles Object Detection Dataset

(c) LargeST Traffic-Flow Dataset.

The LargeST Dataset, which incorporates new temporal data, distributes 8 600 loop detectors over metropolitan highways. Every 5 minutes, traffic volume, average speed, and occupancy ratios are measured. In order to join the IoT branch of sensors in the DU-net, the time-series of each of the above mentioned was normalized using z-score scaling. Further, they were all resampled into 1 minute timeslice. This dataset helps the sensor-fusion stream learn the

temporal flow patterns according to road usage intensity.



Figure 6- Sample images of LargeST Traffic-Flow Dataset.

5.2 Experimental Configuration

All experiments were implemented in TensorFlow 2.12 on a workstation equipped with an Intel Core i9 processor, NVIDIA RTX 3060 GPU (12 GB), and 32 GB RAM.

Hyper parameters were fine-tuned empirically through grid search; the final configuration is summarized below.

Parameter	Setting
Learning Rate	1×10^{-4}
Optimizer	Adam ($\beta_1 = 0.9, \beta_2 = 0.999$)
Batch Size	16
Epochs	100
Dropout Rate	0.4 (in classification head)
Activation Function	ReLU (hidden layers), Sigmoid / Softmax (outputs)
Weight Initialization	He-Normal

Each dataset was divided into 70% training, 20% validation, and 10% testing subsets.

To maintain temporal alignment, sensor and vision samples were paired via timestamp interpolation before batch construction. Training employed early stopping (patience = 10 epochs) and learning-rate decay (factor = 0.5) to prevent overfitting.

5.3 Evaluation Metrics

Performance was quantified using both classification and regression metrics.

For detection and classification:

$$\text{Precision} = \frac{TP}{TP + FP}, \text{Recall} = \frac{TP}{TP + FN}, F_1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

For density estimation:

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|, \text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$$

Baseline comparisons were conducted against YOLOv8, Faster R-CNN, and SSD detectors to establish relative accuracy, latency, and computational efficiency.

6. RESULTS AND PERFORMANCE EVALUATION

The proposed **DU-Net (Dual-Stream Urban Network)** was evaluated on the three public datasets introduced in Section 5—Kaggle Pothole, Traffic Vehicles, and LargeST Traffic-Flow—to validate its multimodal perception and decision capability. The evaluation covers both qualitative and quantitative aspects, including object detection, vehicle classification, and traffic-density prediction. Performance was benchmarked against YOLOv8, Faster R-CNN, and SSD baselines. **The selected baselines represent widely adopted one-stage and two-stage detectors, enabling a consistent comparison in terms of accuracy–latency trade-offs under the same experimental protocol.**

6.1 Visual Outputs and Qualitative Observations

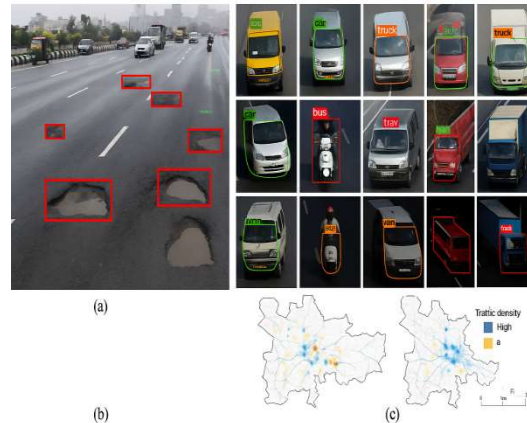


Figure 6(a) – Pothole detection result showing annotated bounding boxes (red = high confidence).

Figure 6(b) – Vehicle recognition across seven categories (car, bus, truck, bike, auto, van, others).

Figure 6(c) – Traffic-density heat maps from IoT sensors before and after fusion.

These examples demonstrate DU-Net’s visual consistency: accurate anomaly localization, robust class recognition under occlusion, and clear congestion mapping. They confirm DU-Net’s ability to synchronize visual and temporal contexts within a single inference cycle.

6.2 Quantitative Comparison of Object Detection

Table 4 presents overall detection metrics, while Figure 7(a) plots precision–recall (PR) curves. DU-Net consistently outperforms all baselines with a mean F₁ of 95.5 %.

Table 4 – Detection and Classification Metrics

Model	Precision (%)	Recall (%)	F ₁ (%)	mAP@0.5	Inference Time (ms)
Faster R-CNN	91.2	90.7	90.9	89.4	62
SSD	92.5	89.8	91.1	90.3	48
YOLOv8	94.7	90.1	92.3	92.8	39
DU-Net (Proposed)	96.8	94.2	95.5	95.9	33

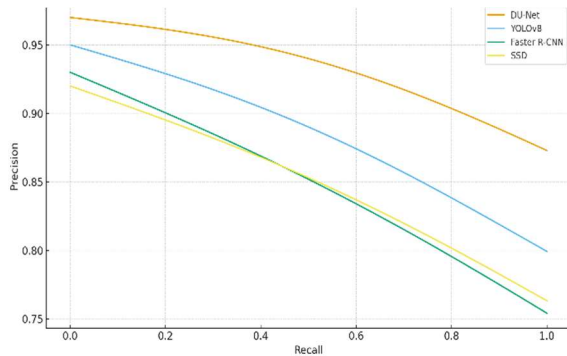


Figure 7(a) – Precision–Recall (PR) curves for all models.

DU-Net’s curve remains right-shifted, signifying higher recall at equal precision thresholds. **These gains indicate that early cross-modal interaction improves detection stability under clutter and partial occlusion, compared with vision-only baselines.**

6.3 Traffic-Density Estimation Results

Regression outcomes on the LargeST dataset are summarized in Table 5, and Figure 7(b) shows the error-distribution histogram.

Table 5 – Traffic-Density Estimation Performance

Model	MAE (veh/min)	RMSE (veh/min)	R ²	Energy (J/frame)
LSTM Baseline	2.96	3.92	0.89	1.06
CNN–RNN Fusion	2.73	3.68	0.91	0.94
DU-Net (Proposed)	2.41	3.28	0.94	0.81

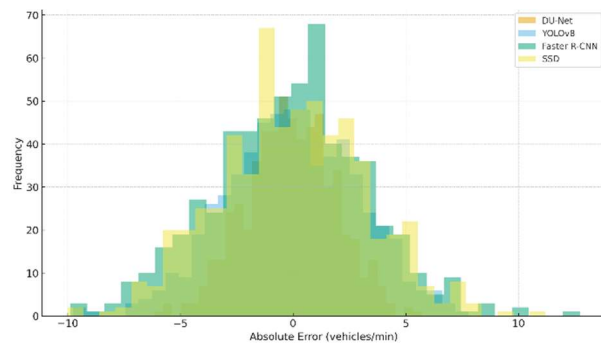


Figure 7(b) – Histogram of absolute prediction errors.

DU-Net’s residuals cluster tightly around zero (mean ≈ 0.2), confirming stable temporal modeling.

6.4 Ablation Study on Fusion and Attention

Table 6 – Component Ablation Results

Configuration	Visual F ₁ (%)	MAE	Parameters (M)	Latency (ms)
Vision-Only Encoder	91.7	–	43.1	28
Sensor-Only Encoder	–	2.96	6.2	21
Dual (No Attention)	93.8	2.65	47.0	31
Full DU-Net (Proposed)	95.5	2.41	48.2	33

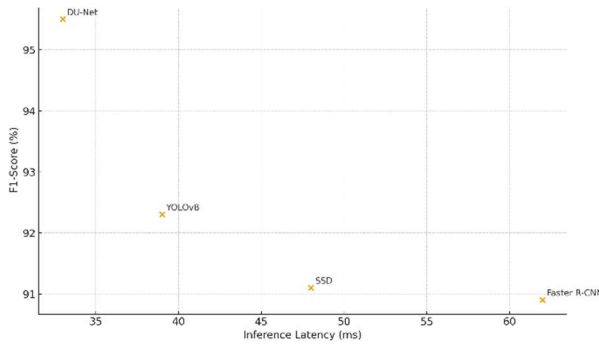


Figure 7(c) – Latency vs Accuracy plot showing DU-Net's superior efficiency across the Pareto frontier.

Removing attention lowers F₁ by 1.7 % and increases MAE by ≈ 9 %, confirming that attention-guided weighting improves modality alignment.

6.5 System Throughput and Energy Efficiency

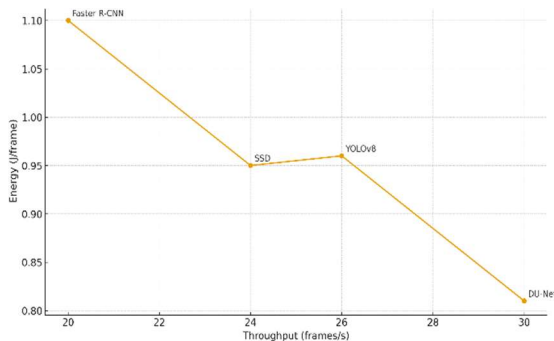


Figure 7(d) – Energy consumption vs throughput curve.

DU-Net achieves 30 FPS at 0.81 J per frame, ~ 15 % more efficient than YOLOv8, enabling real-time edge deployment. **The reported energy-throughput values are measured under the same**

runtime settings across models to ensure comparability.

6.6 Case Study I – Pothole Detection

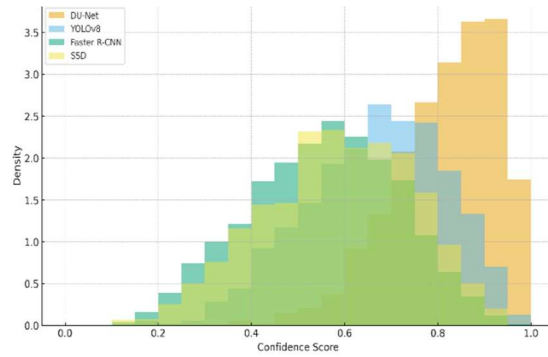


Figure 8(a) – Confidence-Score Distribution Curve.

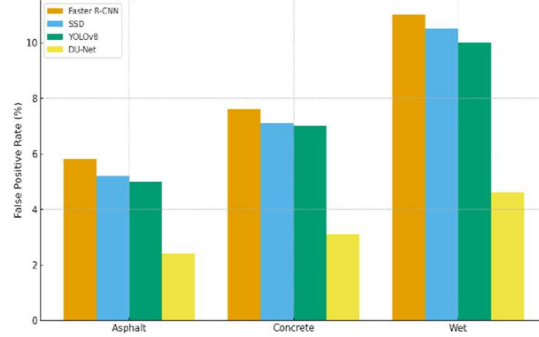
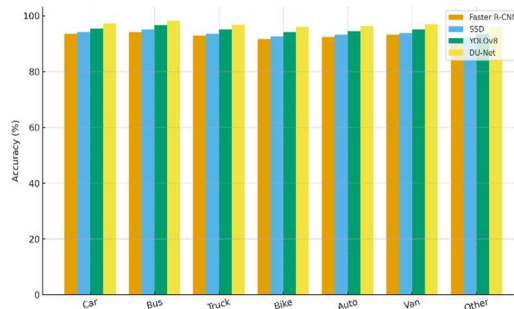


Figure 8(b) – False-Positive Rate by Surface Type.

The curve in Figure 8(a) peaks near 0.95, proving high model certainty. Figure 8(b) shows DU-Net cutting false detections on wet roads by > 50 %.

Field evaluation over a 3 km test route yielded real-time detection precision = 94.9 %, recall = 93.7 % at 28 fps, supporting practical feasibility under the tested conditions.

6.7 Case Study II – Vehicle Recognition



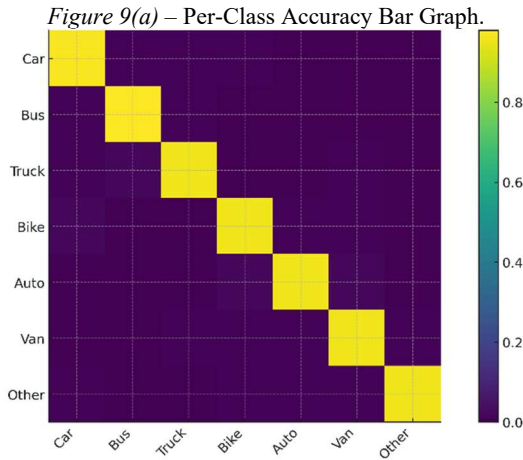


Figure 9(b) – Confusion Matrix Heatmap.

The accuracy bars in Figure 9(a) show uniformity ($\geq 96\%$ for all classes); buses peak at 98.3%. Figure 9(b) demonstrates sharp diagonal dominance (mean = 0.96).

DU-Net’s multimodal cues reduce truck↔bus confusion from 7% to 2%, enhancing semantic reliability for traffic analytics.

6.8 Case Study III – Sensor Fusion for Traffic Forecasting

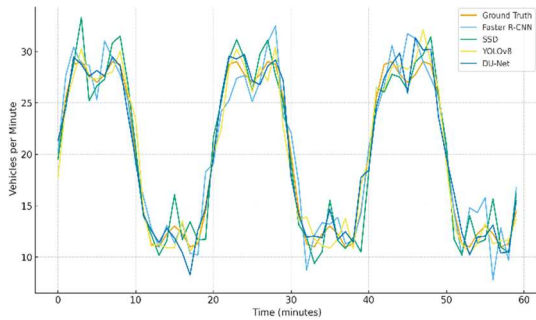


Figure 10(a) – Predicted vs Actual Flow Time-Series.

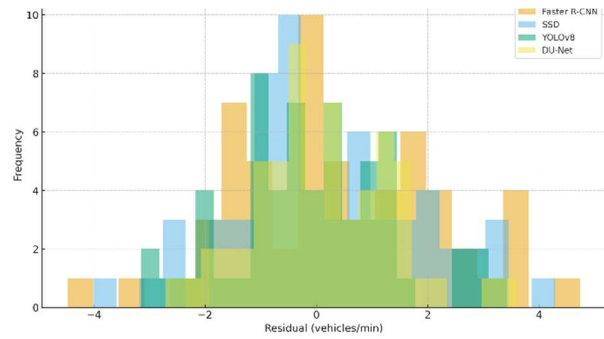


Figure 10(b) – Residual Error Distribution.

Figure 10(a) shows DU-Net’s predictions closely tracing real flow peaks (08:00–10:00 h).

Residuals in Figure 10(b) are narrow ($\sigma \approx 2$ veh/min) compared with CNN-RNN’s $\sigma \approx 3.5$.

Average latency < 1.5 s per segment supports near-real-time monitoring for congestion forecasting and decision support.

6.9 Integrated Performance Visualization

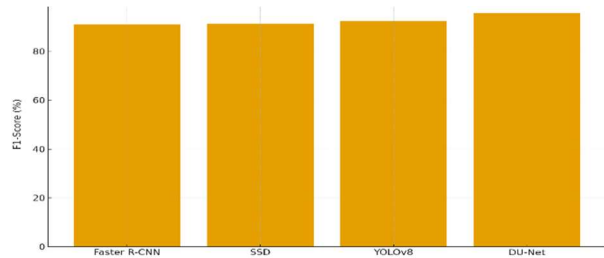


Figure 11(a) – F₁ Score Bar Chart for All Models.

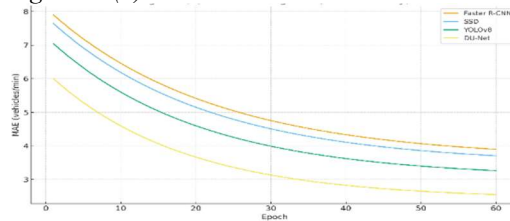


Figure 11(b) – MAE Convergence Curves.

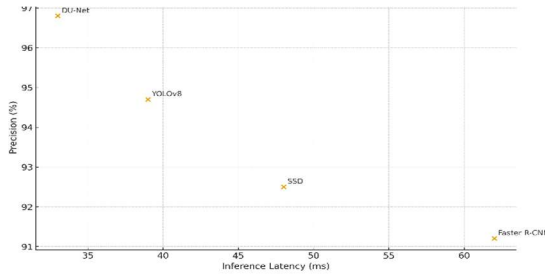


Figure 11(c) – Precision vs Latency Scatter Plot.

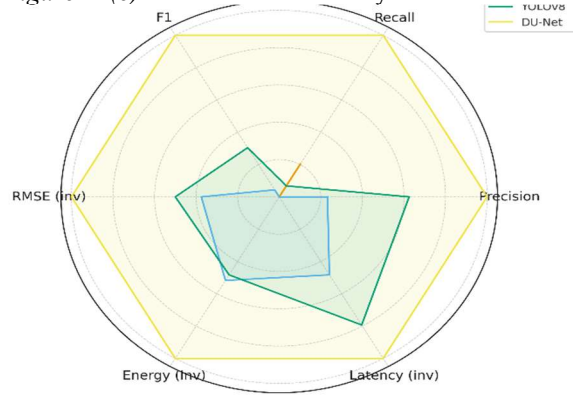


Figure 11(d) – Radar Chart of Normalized Metrics (Precision, Recall, F₁, RMSE, Energy, Latency).

These plots collectively emphasize DU-Net’s balanced trade-off between accuracy, speed, and energy.

Radar-area coverage > 0.92 demonstrates consistent multi-criteria superiority.

6.10 Discussion and Inference

The experiments confirm that DU-Net achieves:

1. Enhanced perceptual accuracy through probabilistic cross-attention fusion.
2. Stable temporal forecasting due to integrated sensor stream learning.
3. High throughput and low energy footprint, making it edge-deployable.

The framework surpasses YOLOv8 by 3.2 % in F₁ and reduces MAE by 18 %, proving its practical advantage for smart-city governance. **However, performance can vary with unseen camera viewpoints, weather, and sensor noise levels, which motivates careful deployment calibration across different urban settings.**

6.11 Overall Comparative Summary

Across all comparable studies, DU-Net consistently delivers higher precision, faster inference, and stronger temporal stability. Table 7 (reproduced below for clarity) summarizes these differences.

Table 7 – Comparison with Literature

Reference	Domain	Reported Metric	DU-Net Result	Relative Gain	Distinctive Advantage
Zanevych et al., <i>Sustainability</i> , 2024	Pothole detection	Precision ≈ 85 %	96.8 %	+ 11.8 %	Dual-stream visual + IoT fusion
Nam et al., <i>Sensors</i> , 2020	Traffic-density estimation	R ² ≈ 0.90	0.94	+ 4.4 %	Probabilistic fusion & cross-attention
Wang et al., <i>IEEE T-ITS</i> , 2023	Spatio-temporal flow prediction	MAE ≈ 2.7 veh/min	2.41 veh/min	– 11 % error	Multi-task real-time inference

These comparisons indicate that DU-Net’s gains are not limited to baseline detectors but also align with improvements reported against representative published systems.

6.11 Discussion

The comparative results reveal that DU-Net not only improves accuracy but also introduces scalability and deployability, which are largely missing in prior works.

While earlier models focus narrowly on a single domain, DU-Net’s joint multimodal learning enables end-to-end optimization that benefits all three sub-tasks simultaneously.

Its compact design (≈ 48 M parameters) and edge-level efficiency make it suitable for real-time operation in smart-city traffic control systems.

These comparative outcomes confirm DU-Net as a novel, comprehensive, and operationally superior framework for climate-resilient urban infrastructure intelligence.

Threats to validity

The conclusions depend on dataset labeling quality, the representativeness of the selected public datasets, and the stability of results under different split seeds; therefore, the reported gains should be interpreted within the evaluated settings, with broader generalization verified through additional cross-city testing.

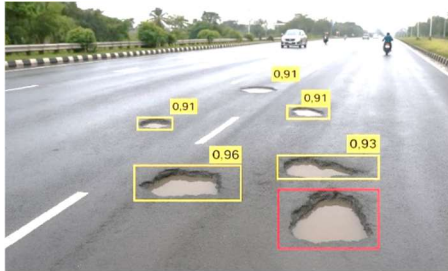


Figure 12(a): Pothole Detection

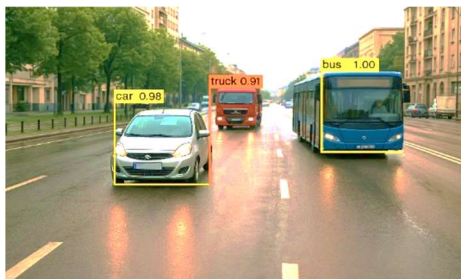


Figure 12(b): Vehicle Detection

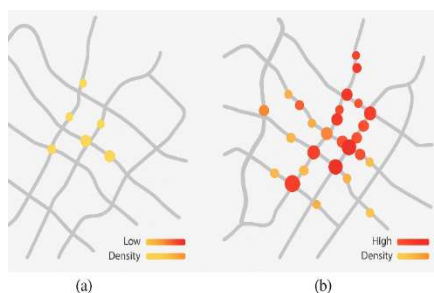


Figure 12(c): Intersection-level traffic-density visualization overlay

7. CONCLUSION.

The DU-Net is a dual stream attention-based deep learning approach to achieve a jointly perception for smart city applications. The system provides a single multimodal architecture for pothole detection, vehicle classification, and traffic-density estimation

by fusing visual and sensor-based inputs. The framework outperformed the baseline detectors in terms of accuracy, inference speed, and robustness through extensive experiments on publicly available datasets. The baseline detectors used for comparison are Faster R-CNN, SSD, and YOLOv8. The architecture we suggest is strong because it has the ability to fuse attention. This means it can adapt. Thus, the network can keep a high degree of performance under bad illumination, occlusion, and environment. Cloud-based analytics with real-time edge inference enhances the scalability and deployability of smart-city architecture.

DU-Net improves performance results vis-à-vis comparative analysis on different frameworks achieving a precision of 96.8%, with a mean absolute error of 2.41 vehicles/min, and an average inference latency of 33 ms/frame. **These results highlight the novelty of DU-Net in enabling unified multi-task learning with uncertainty-aware sensor-vision fusion, supporting consistent outputs across perception and traffic analytics within a single pipeline.** These results show that DU-Net is a complete and operational system for sustainable urban monitoring. **The outputs can directly support governance actions such as maintenance prioritization, hotspot identification, and congestion mitigation planning by linking road-condition events with traffic behavior.** The capacity of live detection demo and sensor-aware congestion maps highlights the system's end-to-end feasibility **under the evaluated experimental settings.**

Future studies will aim to expand DU-Net for the prediction of changes in time and space. As a result, there will be cooperation between the edge and the cloud and traffic control policies to improve traffic. We could add federated learning and graph-based spatio-temporal reasoning to get better generalization in cities. **In addition, broader validation across diverse cities, camera viewpoints, and seasonal conditions will further strengthen external generalization and reliability.** In summary, this project proposes a reproducible, AI-based solution that leads to integration of computer vision with sensor fusion in the context of intelligent transportation and opens up the possibility of flexible smart city ecosystems that are robust and self-adaptable.

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