

# i.mobilitathon 5.0

Driving innovation to create **smarter,**  
**scalable solutions**

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**Problem Statement : Road Hazard Detection & Real-Time Alerts.**

# Brief About The Idea

## Current Challenges in Road Hazard Detection



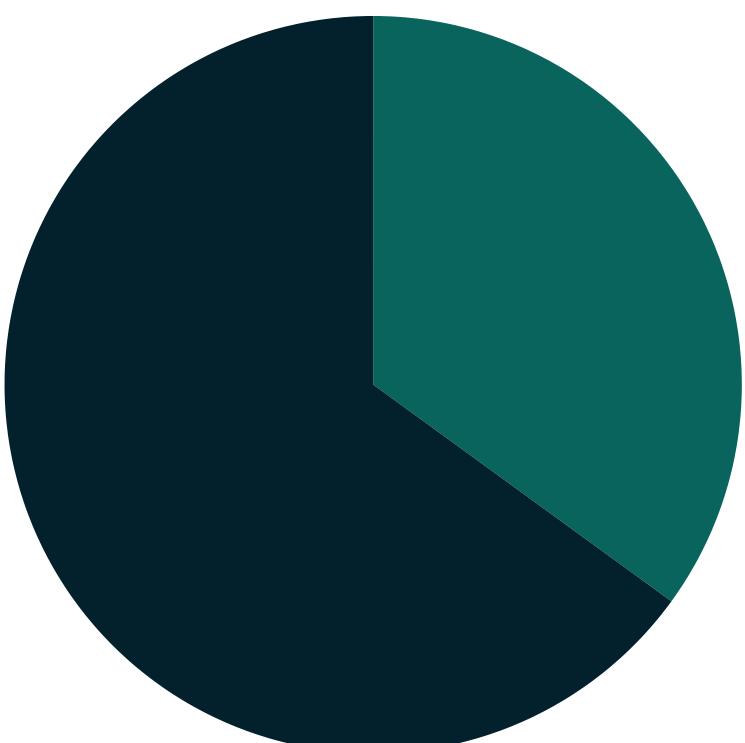
### Fragmented and Manual Reporting

No unified national platform exists. Most systems rely on **manual user submissions**, leading to incomplete and delayed hazard data.

Over **1.55 lakh** people lose their lives every year on Indian roads that's **425 deaths per day**.

● Organization With Methods

● Organization Without Methods



### Lack of Real-Time Detection

Existing solutions don't provide **instant notifications** to nearby drivers. Without **low-latency AI inference**, even a few seconds' delay can result in **avoidable accidents**, especially at highway speeds.



### Limited Infrastructure Coverage

Smart cameras cover only highways and cities. Over **70% of India's roads**; mainly rural areas lack automated monitoring.



### Privacy & Data Sensitivity

Dashcams capture faces and number plates. Few systems apply on-device **anonymization**, raising privacy concerns.



### Duplicate Or False Alerts

Multiple vehicles may flag the same hazard, creating spam or **false positives**. No clustering or validation is used.

● Causes of Road Accidents in India (2023)

Dangerous driving / Overtaking

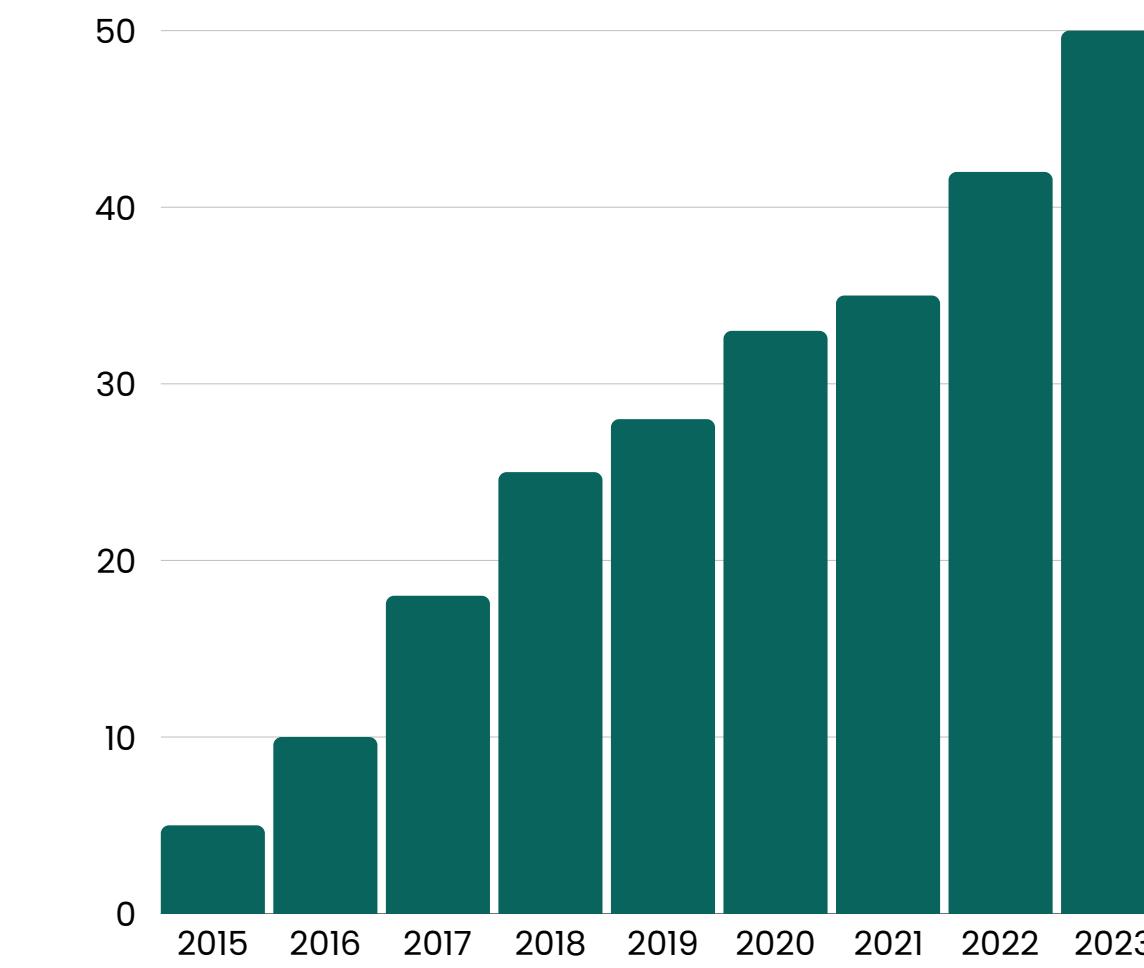
Poor road condition

Vehicle defect / stall

Distance Error

Other

● Artificial Intelligence in Self-Driving Cars

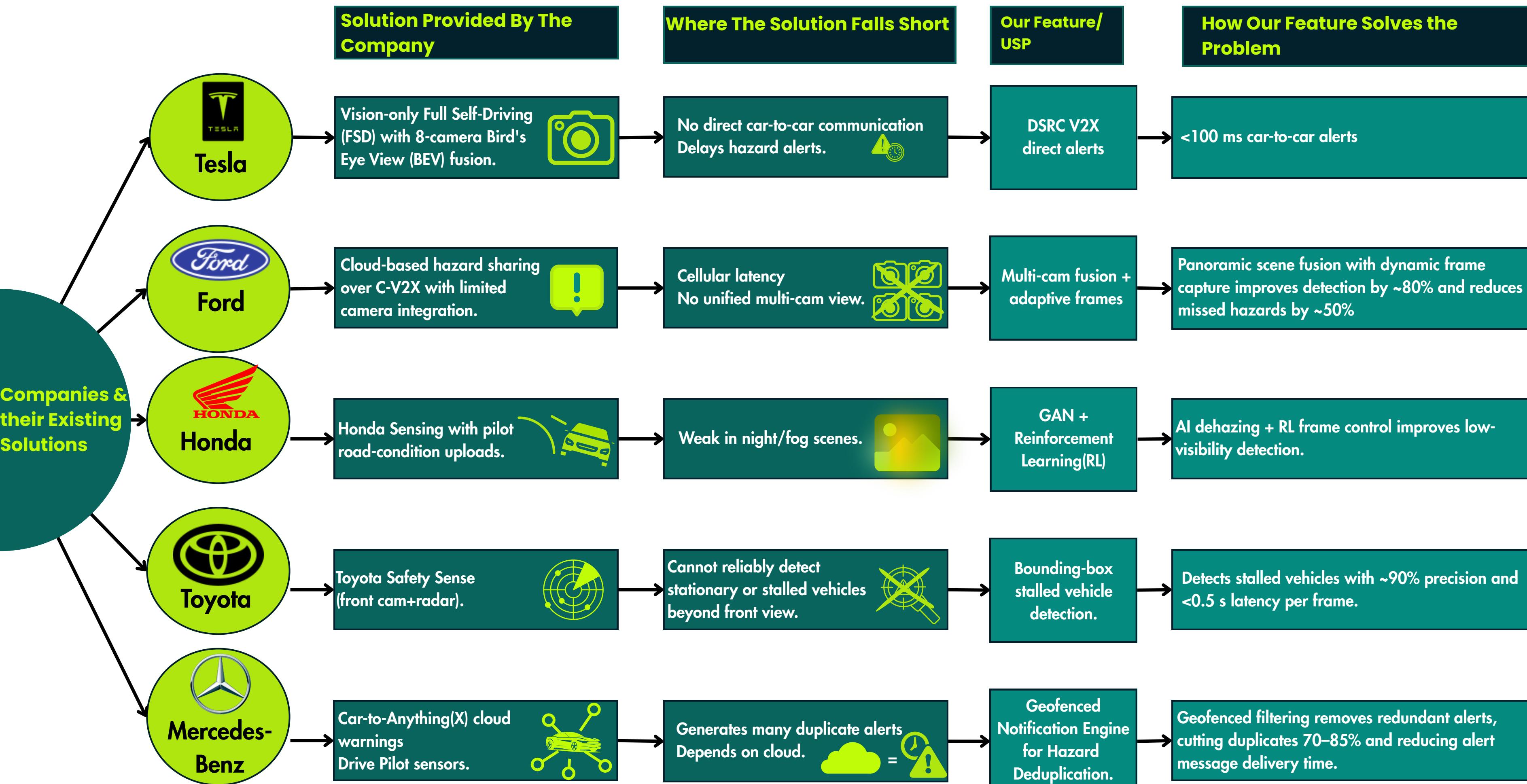


India loses **₹20,000+ crore** each year in productivity, logistics delays, and vehicle damage caused by poor road infrastructure.

More than **4.3 lakh** people suffer injuries annually due to crashes, often caused by potholes, debris, or stalled vehicles.

The average pothole repair time is **2–3 weeks**, even after complaints are logged.

# Opportunities



# List Of Features Offered By The Solution

## 1 Composite Image Stitching + Image Enhancement

- **Unified Input:** Multiple camera feeds are stitched into a single panoramic frame.
- **Reduced Load:** One composite image is analyzed per timestep.
- **Seamless Coverage:** Tiling/homography ensures smooth scene coverage.
- **Enhanced Visibility:** GAN-based dehazing and brightening handle fog, glare, and low light.
- **Improved Detection:** Hazard detection is boosted in adverse and low-visibility conditions.

## 2 Adaptive Key Frame Sampling And Capture Control

- **AI-Driven Selection:** AI selects keyframes based on scene changes, motion, and object appearance.
- **Dynamic Capture:** Captures only informative frames skipping static or repetitive input.
- **Efficiency Focused:** reduces unnecessary processing in slow, stop-and-go, or idle scenarios and prioritizes events at higher speeds or during rapid change.
- **Optimized Processing:** Uses a relevance-and-coverage optimization, scoring frames in real-time delivering up to 60% less compute with robust, real-time analytics and no system overload.

## 3 Efficient Backbone Neural Network

- Deploys the advanced DEIMv2-S transformer backbone for more accurate feature extraction.
- Delivers up to 51 mAP on COCO-style benchmarks; outperforming YOLOv11 by 4–8% in real-world hazard detection tasks.
- Maintains real-time performance (30–170 FPS) even on embedded GPUs or edge devices.
- Reduces false positives and improves detection of medium and large road hazards (potholes, debris) compared to older CNN models.

## 4 Multi-Head Inference:

- Implementing **multi-head** inference for **parallel** specialized vision tasks.
- Includes: Object Detection Head, Segmentation Head, Depth Estimation Head, Object Tracking Head, Road/Lane Mask Head, Few-Shot Hazard Head and Privacy Blur Head.

## 5 Fusion Engine (AI/Rule-Based):

- **Multi-Head Input:** Receives outputs from all specialized vision heads.
- **Decision Logic:** Fuses signals using rules or an ML model to validate hazards.
- **Hazard Scoring:** Produces a Hazard Confidence Score and severity level.
- **Purpose:** Ensures only true hazards are flagged, improving detection reliability.

## 6 On-Device Alert System

- **Visual Alert:** On-screen pop-up or AR overlay showing hazard type and distance.
- **Audio Alert:** Spoken warning or distinctive sound to grab driver attention.
- **Context-Aware:** Timing adjusts based on vehicle speed and hazard distance to ensure relevance.

## 7 Duplicate Alert Suppression

- **Vehicle-side logic:** Tracks recently alerted hazards by ID or location in a short-term cache.
- If a new alert matches one given in the last 5 minutes, it is ignored.
- Prevents multiple cars broadcasting the same hazard from spamming alerts.
- Cloud-side logic ensures that the same user does not receive multiple notifications for the same hazard within a specified timeframe.
- If both V2X and cloud deliver alerts, the app automatically deduplicates them.

## 8 Automated Data Sharing (Dual Mode)

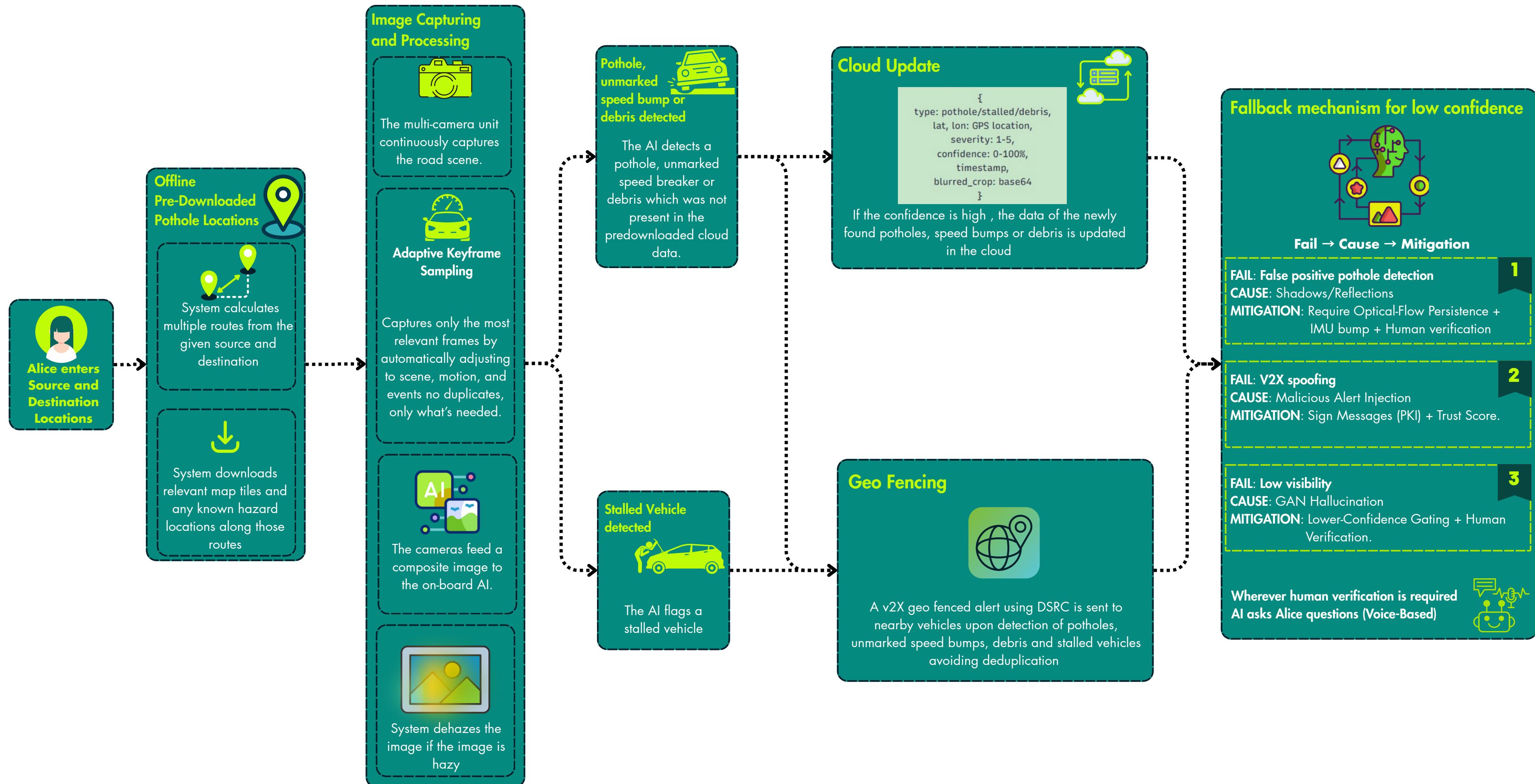
- **V2X Broadcast:** Sends hazard info to nearby vehicles (300–500m) using DSRC/C-V2X and standard format (DENM).
- **Cloud Upload:** Sends hazard ID, location, type, blurred image via HTTPS/MQTT. Minimal data allows 3 G transmission or patching later.

## 9 Cloud-Based Hazard Aggregation

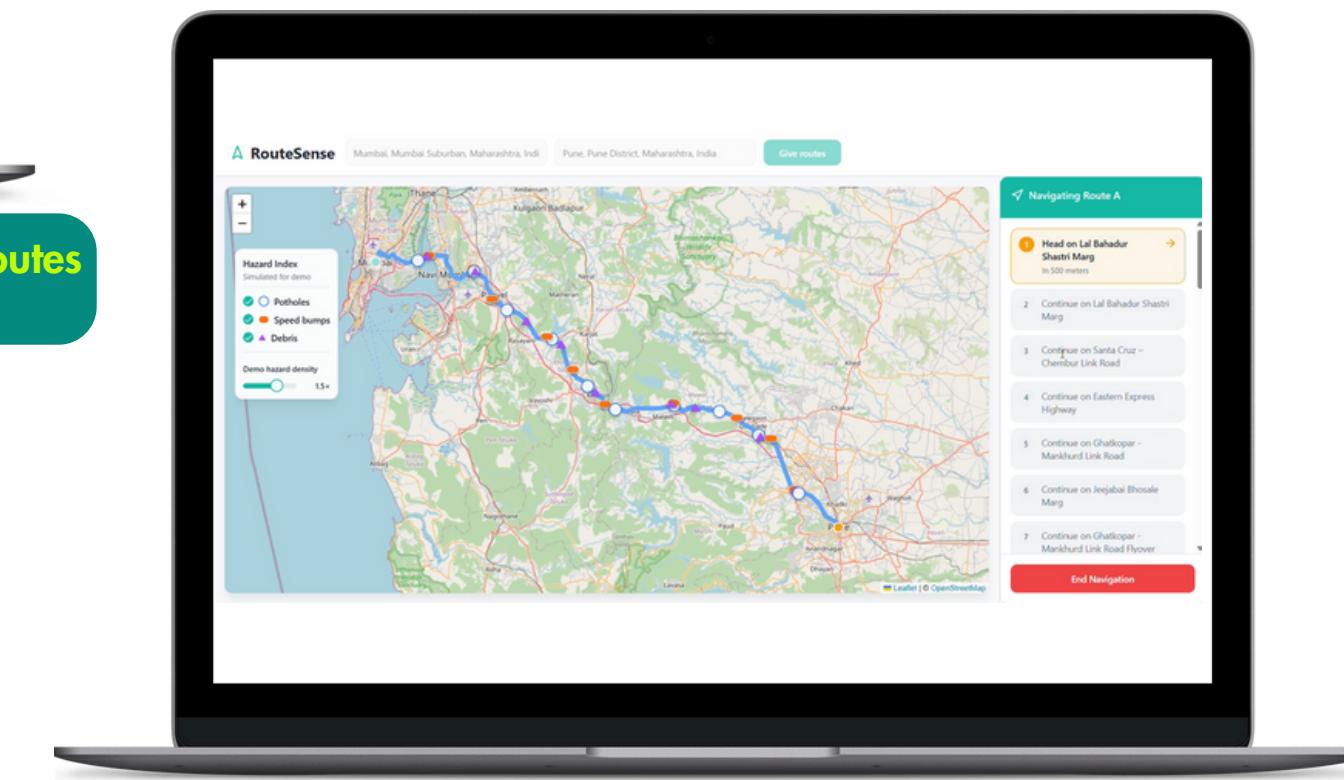
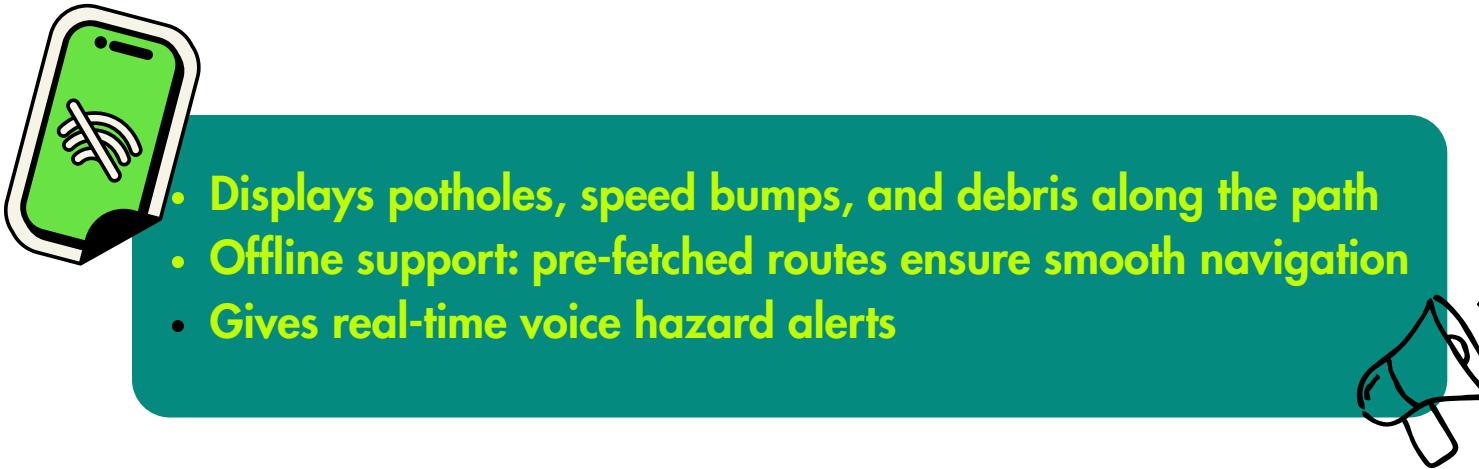
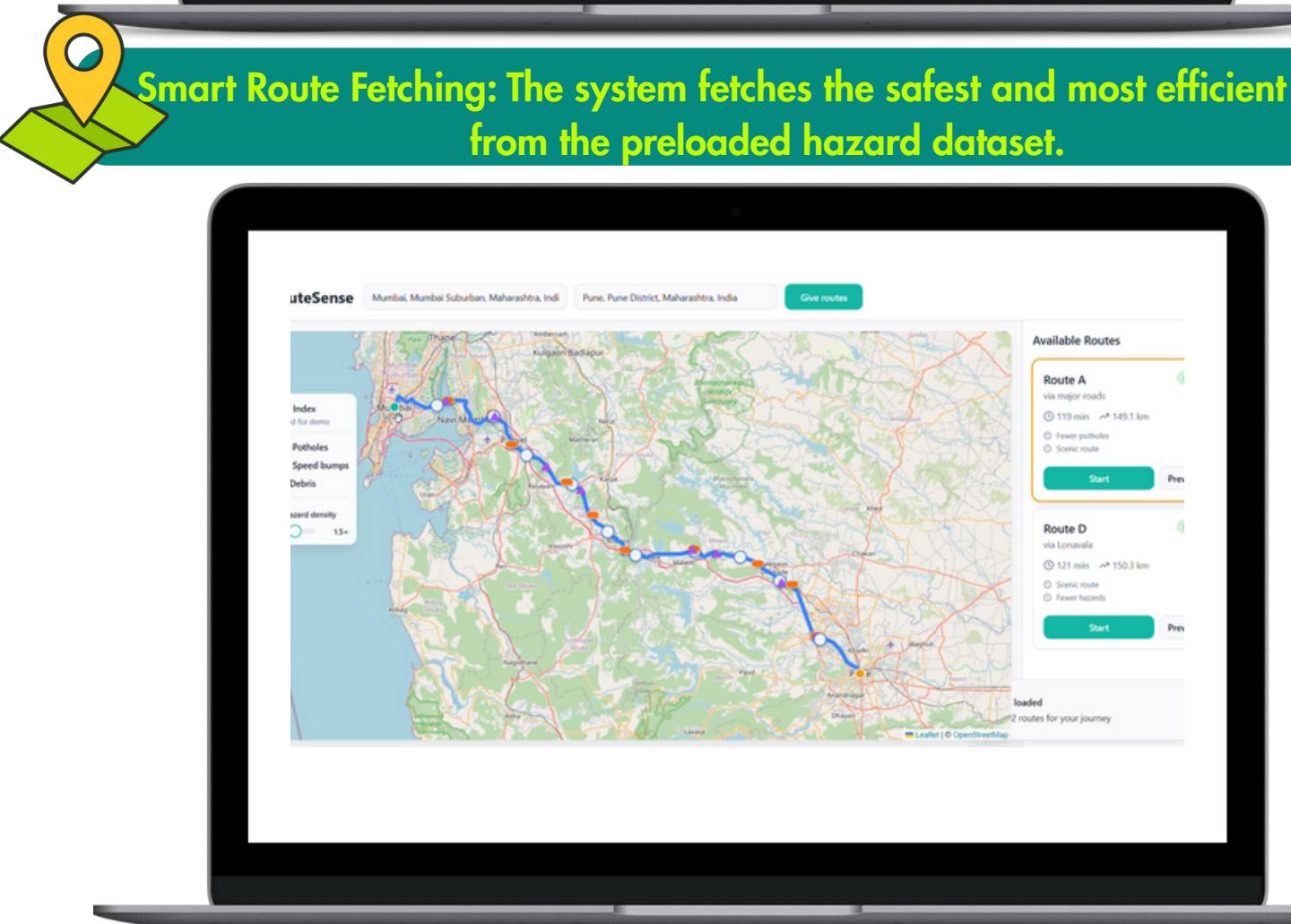
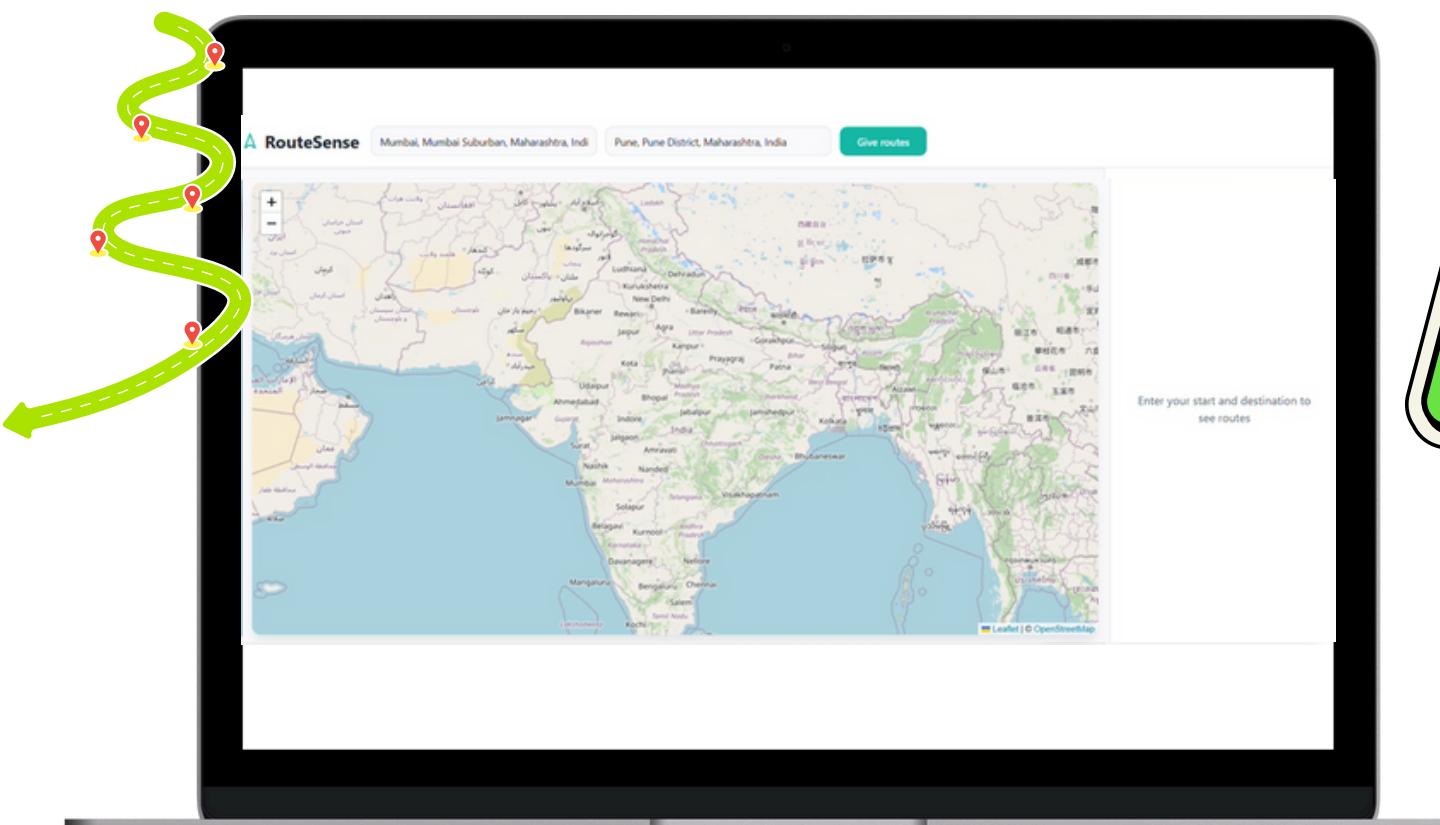
- **Clustering & Filtering:** Groups hazard reports by location and time to remove duplicates and flag unverified hazards.
- **Hazard Database & Map:** Maintains real-time info on hazards, including status (active/fixed/verified), severity, last seen, and number of confirmations.
- **Swarm Verification:** Confirms hazards after 2+ independent reports; critical hazards can trigger alerts immediately.
- **Distribution:** Pushes verified hazard info to approaching drivers as a backup to V2X, ensuring long-range awareness and safety.

## 10 Offline Hazard Caching

- If a destination is set, the app can download hazard info along the route.
- Works even if connectivity drops, ensuring drivers still receive alerts.
- Uses predictive caching of map tiles and hazard points (similar to offline Google Maps).
- Provides continuous service in low-signal or offline areas.



**Start & End Location Input:** Driver enters source and destination



**Voice-Based Verification (Low Confidence)**

"Is there a pothole here?"



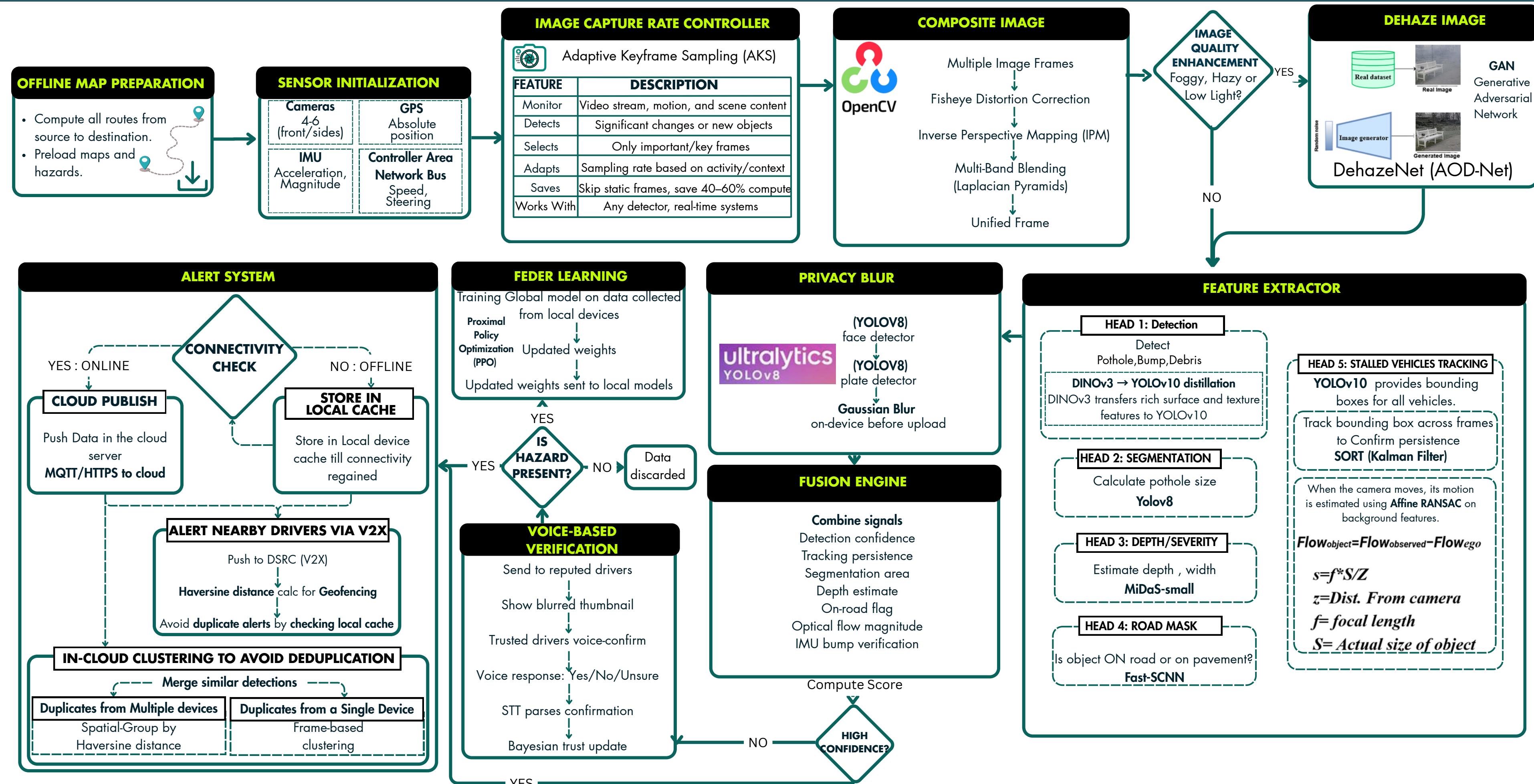
Driver Response: Yes / No / Unsure

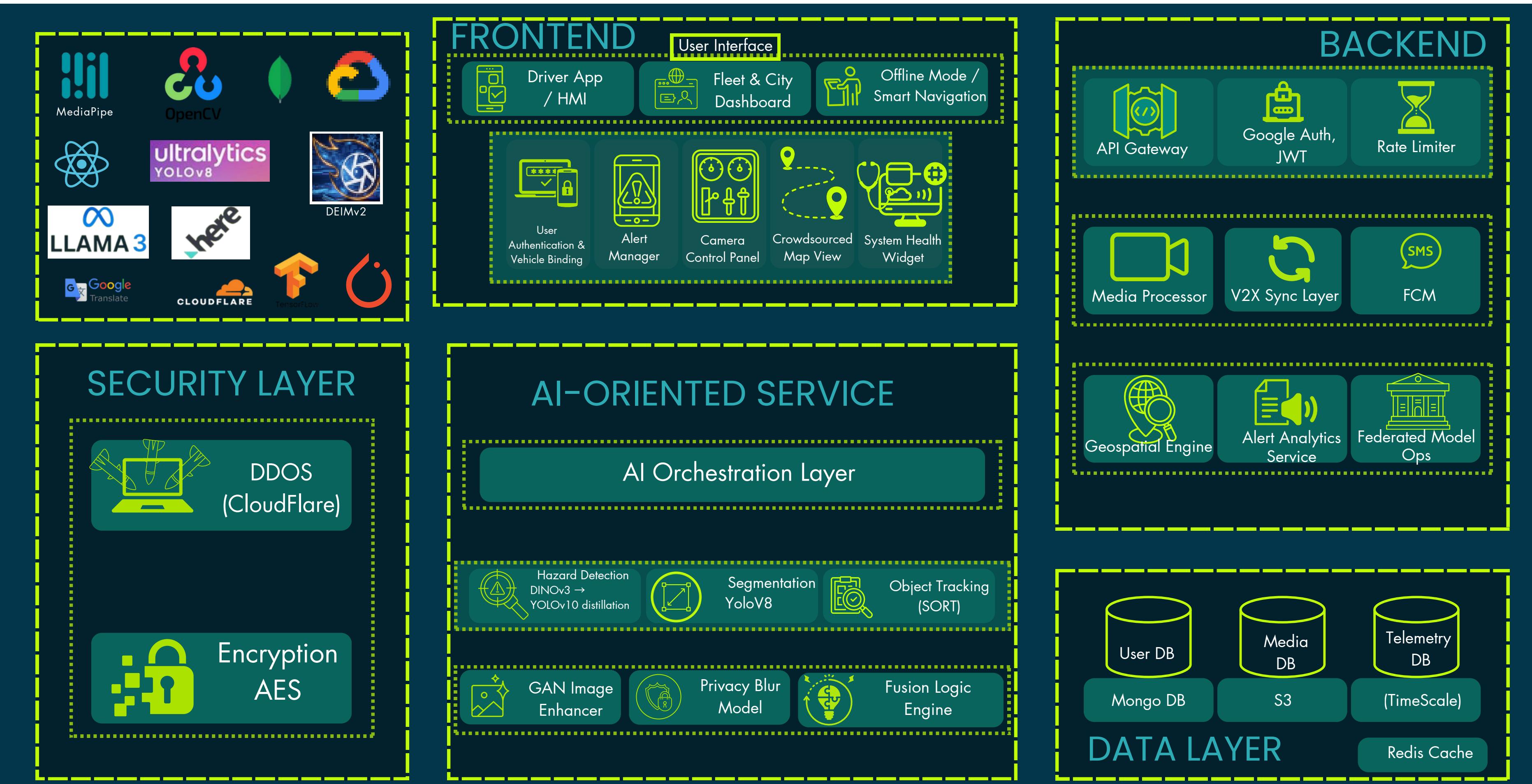


1. Converts speech to text (STT).
2. Updates hazard confidence using Bayesian trust logic.
3. Uploads confirmed hazards to server; discards false ones.

**Ensures only verified road hazards are stored while preserving driver privacy.**

# Architecture Diagram



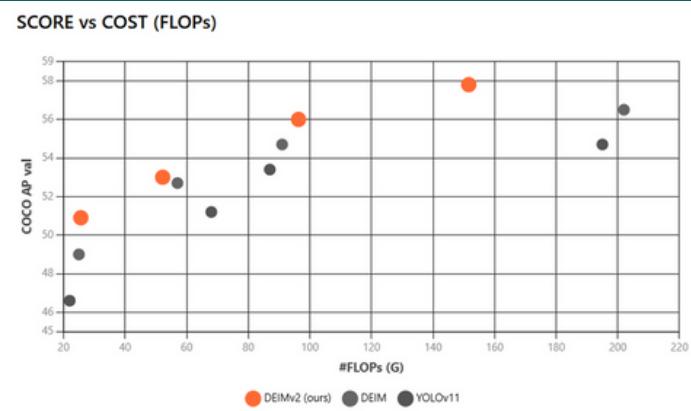


# Estimated Implementation cost

### Unit Economics – Per Vehicle / Year

Cost Item	OEM-Integrated (VW SoC)	Notes
Hardware amortization	₹0	VW path uses built-in SoC/cameras/IMU
Edge software license & support	₹2,500 – ₹5,000	Edge agent, SLA, diagnostics
Cloud & APIs (PostGIS/MQTT/analytics)	₹400 – ₹1,000	Low payloads (DENM + metadata)
Security & privacy ops (PKI, DP/FL)	₹500 – ₹1,000	Keys, audits, SecAgg rounds
Model updates & MLOps	₹600 – ₹1,500	OTA, eval, ablations
Connectivity	₹0 – ₹1,200	DSRC OPEX = ₹0; SIM fallback optional
Total / vehicle / year	₹4,000 – ₹9,000	OEM path = lowest TCO

**SCORE vs COST (FLOPs)**



Powered by Meta's DINOv3 backbone, DEIMv2 demonstrates superior accuracy-efficiency tradeoffs across all FLOP scales.

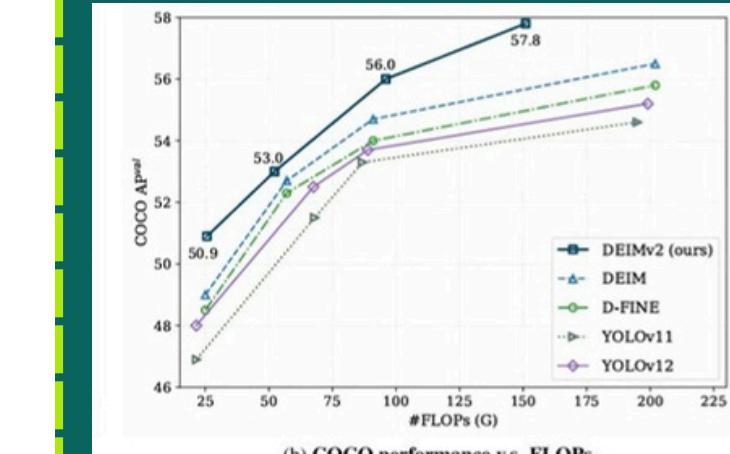
Volkswagen already runs CARIAD software on in-car SoCs. We follow the same model software-only, no additional hardware.

### Competitive Cost Benchmark – Annual Per Vehicle

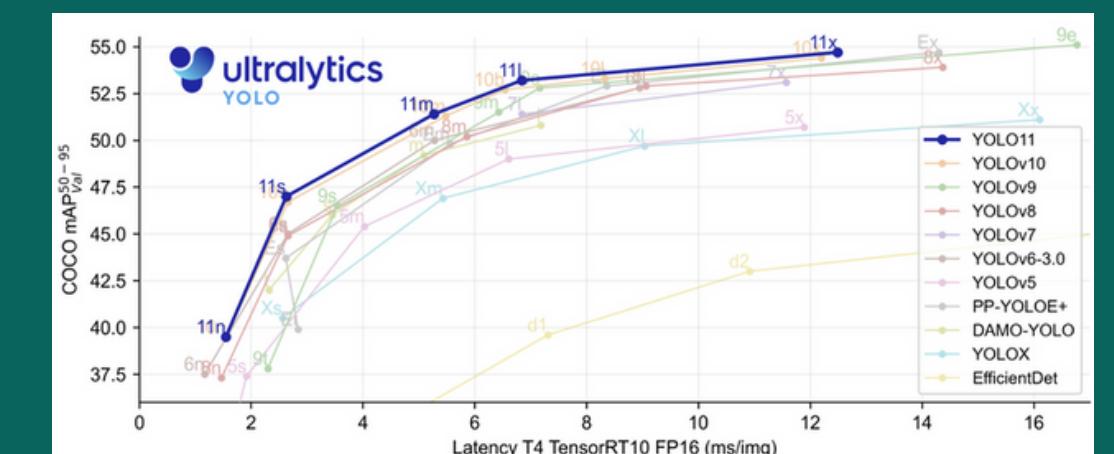
Solution	Type	Annual Cost (₹)	What Is Included
QuISK (OEM, DSRC)	Software-only on VW SoC	4,000 – 9,000	DSRC alerts, geo-dedup, privacy, cloud, updates
Nexar-class dashcam + cloud	Device + subscription	18,000 – 22,000	Cellular cloud alerts; single-cam
Mobileye 8 Connect	Aftermarket ADAS + service	18,000 – 25,000	Service; HW extra/varies
Ford BlueCruise	OEM subscription	~42,000	Hands-free assist (no DSRC hazards)
Tesla FSD (Supervised)	OEM subscription	~1,01,000	Vision ADAS (no DSRC hazards)

### Comparative analysis YOLO vs DEIM

(b) COCO performance v.s. FLOPs.



ultralytics YOLO

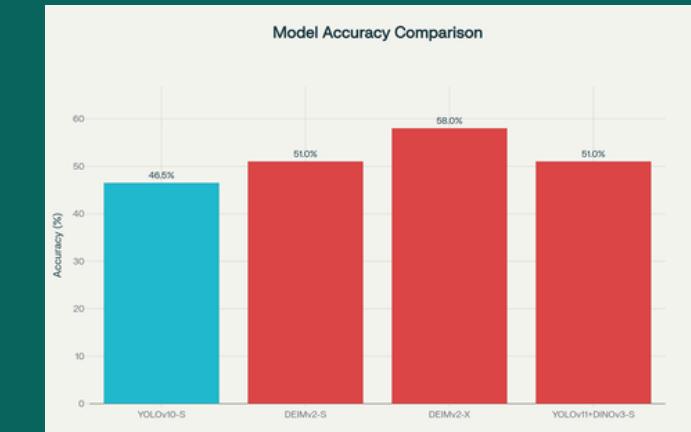


Metric	YOLOv10	YOLOv10+ DINOv3-S	Comment
mAP (50-95)	~41.0%	41.8%	+0.8 percentage point gain ≈ 2% improvement with DINOv3
Parameters (M)	7.2	7.2	Same size but more accuracy per parameter
GFLOPs (B)	21.4	21.4	Slightly more compute but same efficiency DINOv3 & STA modules
Inference Speed (GPU)	5.5 ms	5.6 ms	Still real-time ; 2x more accuracy per ms
Medium Object Accuracy	~48-50%	~52-55%	Better for potholes & debris (medium-sized objects)
Large Object Accuracy	~72-74%	~75-79%	Catches entire hazards (road blocks / barriers); improved speed bump detection
Small Object Accuracy	~28-30%	~30-35%	Similar; still okay for distant hazards
Compute Efficiency	-	~ 60 % FLOPs reduction vs Transformers	Faster than pure attention models; practical on vehicle SoC

**FLOPs:** Floating Point Operations measures the computational cost or complexity of a model.

**COCO:** Common Objects in Context a benchmark dataset for object detection and segmentation.

Model Accuracy Comparison



# Snapshots of the Prototype

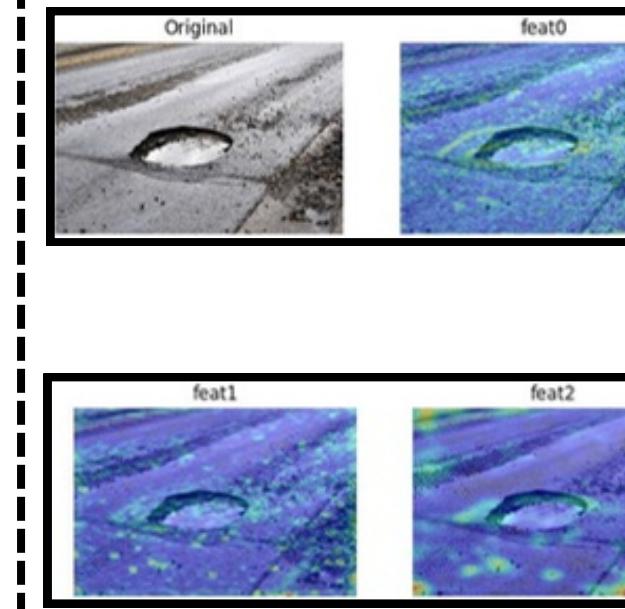
## IMAGE CAPTURE RATE CONTROLLER

### Adaptive Keyframe Sampling (AKS)



**Impact:** Achieved up to 60% reduction in compute load and latency while preserving critical scene information for real-time analysis.

## COMPOSITE IMAGE



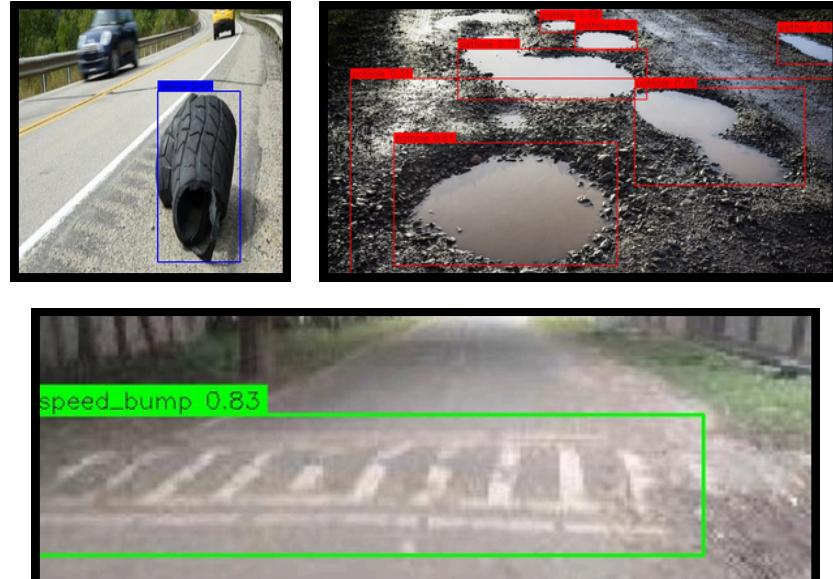
## DEHAZE IMAGE

$$\text{clean} = \text{ReLU}((x_5 * x) - x_5 + 1)$$



**Impact:** Enhance low-visibility (foggy/hazy) road images using a lightweight **DehazeNet (AOD-Net)** to restore clarity for accurate detection.

## H1: ROAD HAZARDS DETECTION



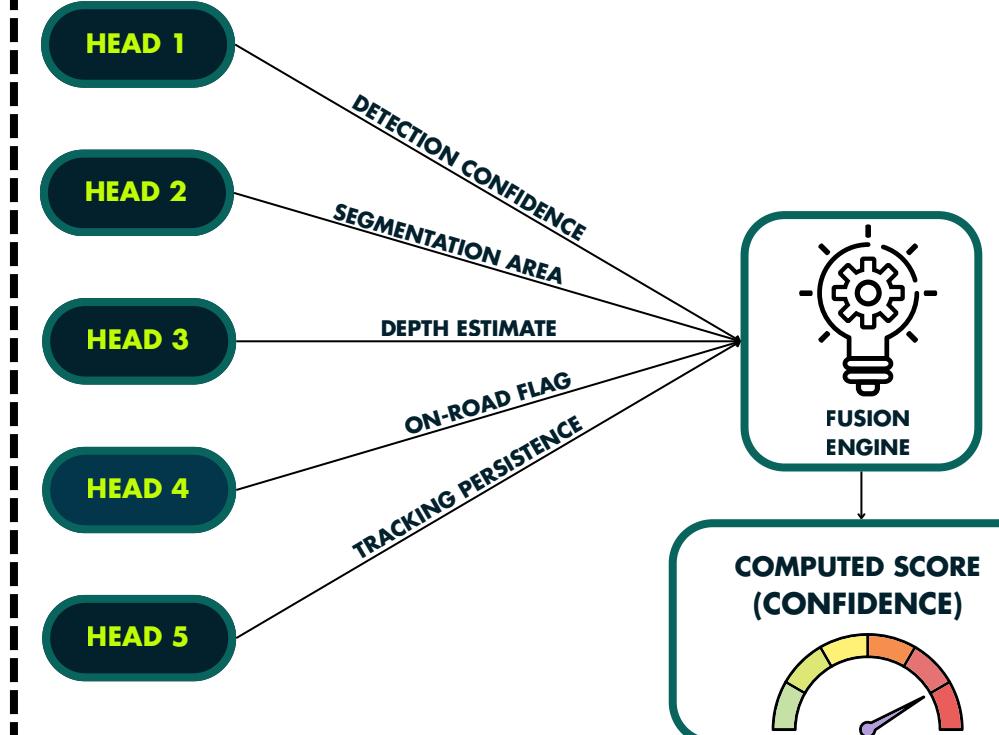
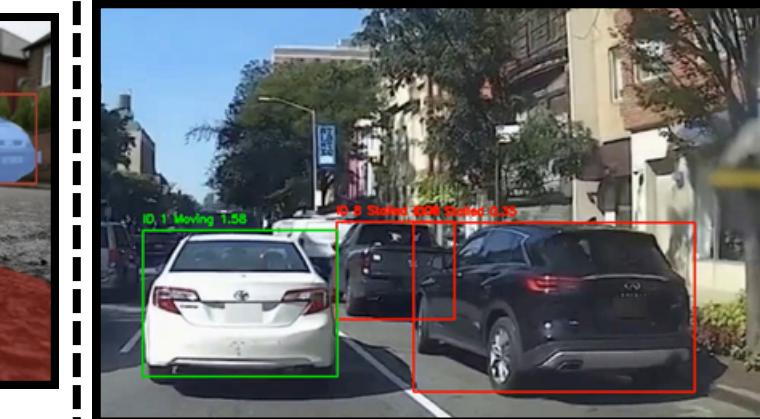
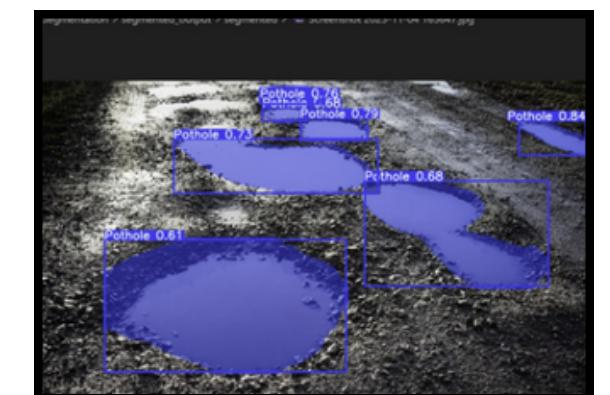
## H2: SEGMENTATION

### H3: DEPTH ESTIMATOR

### H4: ROAD MASK

### H5: STALLED VEHICLE

## FUSION ENGINE



**Impact:** To detect and segment potholes from road images using a trained YOLOv8-Segmentation model

Precision: 0.76

Recall: 0.59

mAP50: 0.72

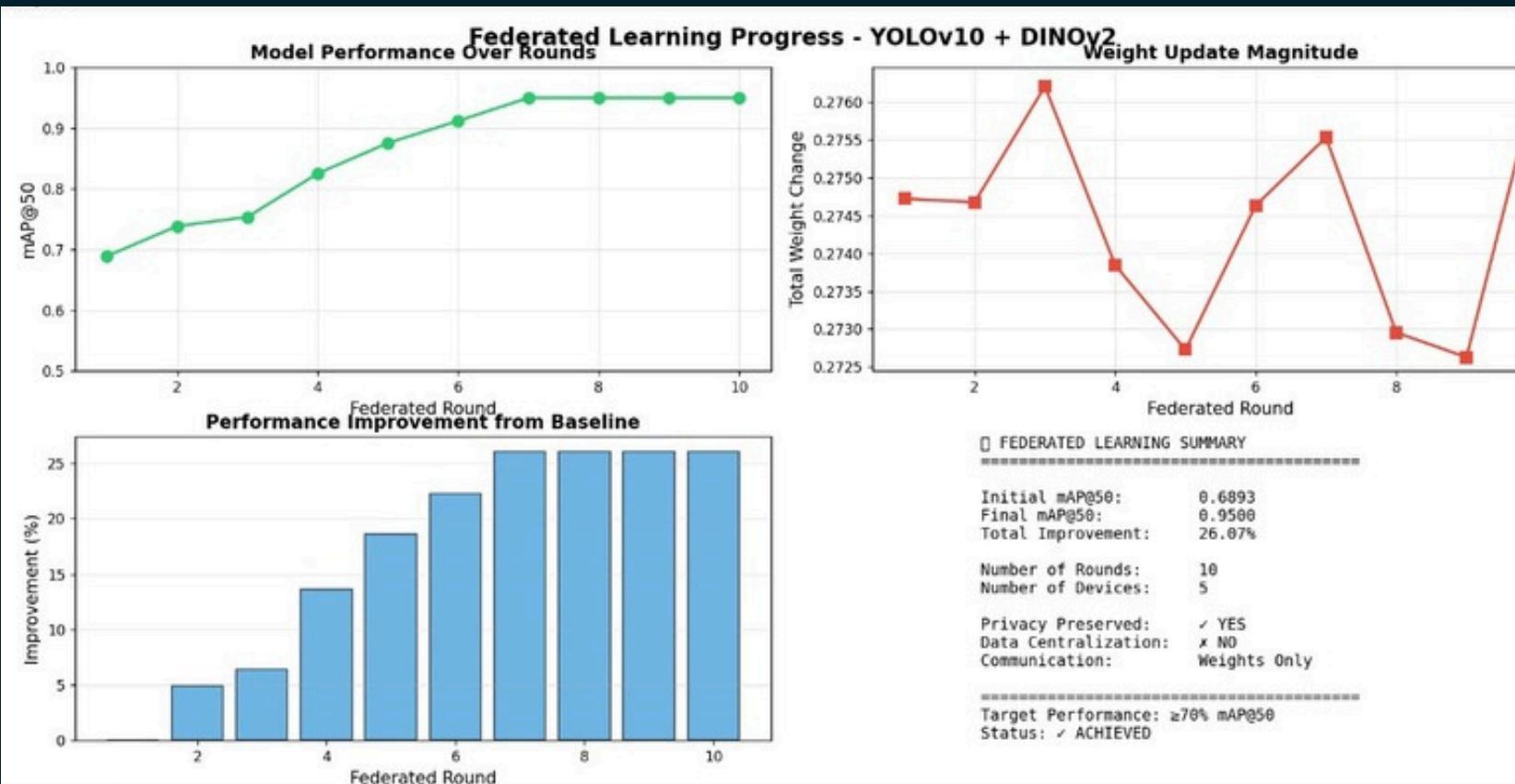
mAP50-95: 0.45

**Impact:** To accurately estimate each pothole's **depth**, **width**, and **area** using **MiDaS-small**, classify its severity level, and enable real-time, data-driven road maintenance for improved safety and repair prioritization.

**Impact:** By integrating **Fast-SCNN** with **YOLO segmentation**, our system intelligently determines whether each detected object : pothole or vehicle lies on the road or pavement, enabling accurate scene understanding for automated safety analytics.

**Impact:** An AI-based vision system that detects truly **stalled vehicles** by compensating camera motion through **affine RANSAC**, **EGO motion** and analyzing residual optical flow for persistent low-motion objects.

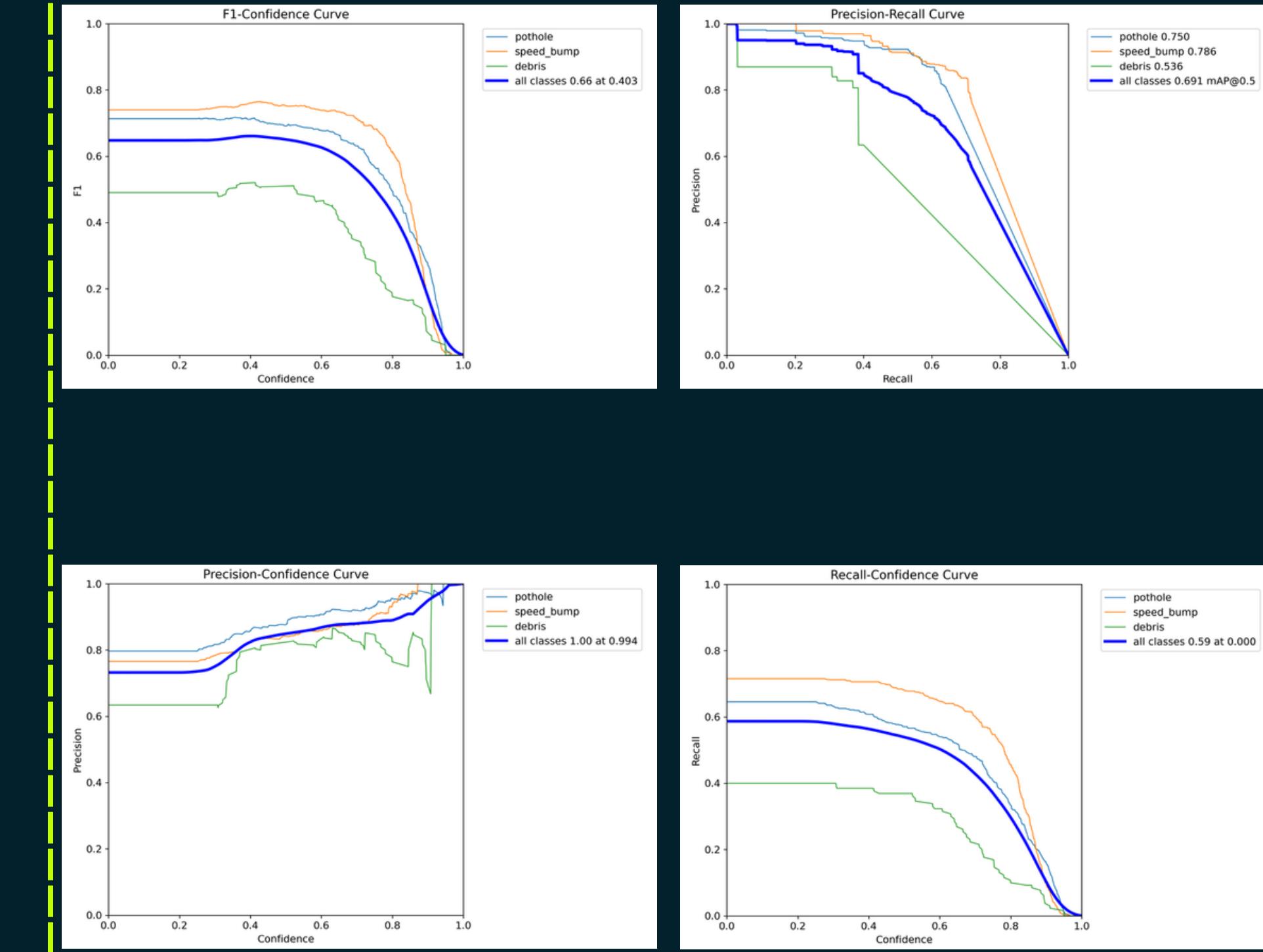
## Proximal Policy Optimization(RL Based)



Class	Images	Instances	Box(P)	R	mAP50	mAP50-95
all	1118	1676	0.83	0.566	0.681	1.00
pothole	286	906	0.863	0.608	0.71	0.508
speed_bump	582	640	0.825	0.76	0.787	0.425
debris	38	130	0.803	0.385	0.567	0.322

Speed: 1.5ms preprocess, 5.5ms inference, 0.0ms loss, 0.1ms postprocess per image

## Model Performance Curves for Road Hazard Detection



Challenges	Description	References & Citations
<b>False Positives in Hazard Detection</b>	Even with bounding boxes, proximity, and lane checks, parked or temporarily stopped vehicles (like delivery vans or cars at signals) can still be misclassified as stalled. This highlights the challenge of modeling context when motion cues are limited.	1. Zhang, H., et al. (2018). <i>DehazeNet: End-to-End Dehazing with AOD-Net</i> . IEEE TIP.
<b>V2X (DSRC) Communication and Geofencing Errors</b>	DSRC alerts depend on precise geofencing to warn nearby drivers. In dense or low-connectivity areas, overlapping signals and weak GPS can cause duplicate or missed alerts, making reliable clustering and deduplication a key challenge.	2. Redmon, J., et al. (2023). <i>YOLOv10: Unified Detector for Edge Applications</i> . arXiv:2403.20325.
<b>Occlusion in High-Traffic Conditions</b>	In heavy traffic, the camera's field of view may be partially or fully blocked by other vehicles, limiting visual detection of potholes, debris, or stalled cars ahead. In such scenarios, reliance shifts to IMU and sensor fusion data, but this transition introduces uncertainty and latency in decision-making.	3. Caron, M., et al. (2023). <i>DINOv3: Self-Distillation with Vision Transformers</i> . arXiv:2305.13785.
<b>Detection on Uneven or Patchy Roads</b>	Small potholes or shallow surface damages can be difficult to identify due to subtle depth variations and visual similarities with shadows or water patches. This makes accurate detection challenging for depth estimation models like MiDaS, especially in low-light or rain conditions.	4. Ranftl, R., et al. (2021). <i>MiDaS: Accurate Monocular Depth Estimation</i> . CVPR.
<b>Debris Classification Ambiguity</b>	Distinguishing harmless objects (like paper bags) from hazardous debris (like stones or metal) needs fine-grained classification. Varying shapes, motion, and low-contrast images often lead to misclassification.	5. Howard, A., et al. (2019). <i>Fast-SCNN: Fast Segmentation for Embedded Devices</i> . arXiv:1902.04502.
<b>Environmental Variability</b>	Lighting, fog, rain, or dust can significantly degrade camera-based performance, even with enhancement models like DehazeNet. Continuous domain adaptation is required to sustain reliability across varying environmental conditions.	6. Schulman, J., et al. (2017). <i>Proximal Policy Optimization Algorithms (PPO)</i> . arXiv:1707.06347.
<b>Feedback Loop Stability &amp; Model Drift</b>	Reinforcement learning from local feedback can unintentionally overfit to region-specific or driver-specific data. Without a proper aggregation strategy, global model weights may drift, reducing consistency across environments.	7. Fischler, M., & Bolles, R. (1981). <i>Random Sample Consensus (RANSAC)</i> . Communications of the ACM.

Demo video URL:

<https://youtu.be/GqcZbpZZlc0>

GITHUB: <https://github.com/Achintya1800/Volkswagen-imobilothon-5.0-QUISK>



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