Team Name : Quisk

Team Leader Name : Asmiya Sayyad

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.

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.

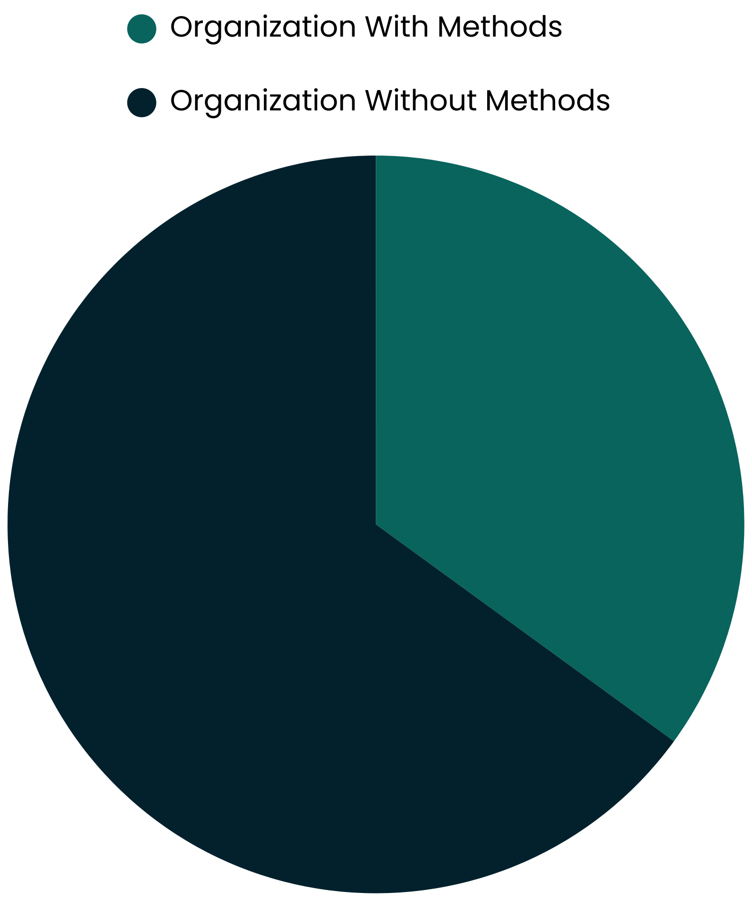
Privacy & Data Sensitivity

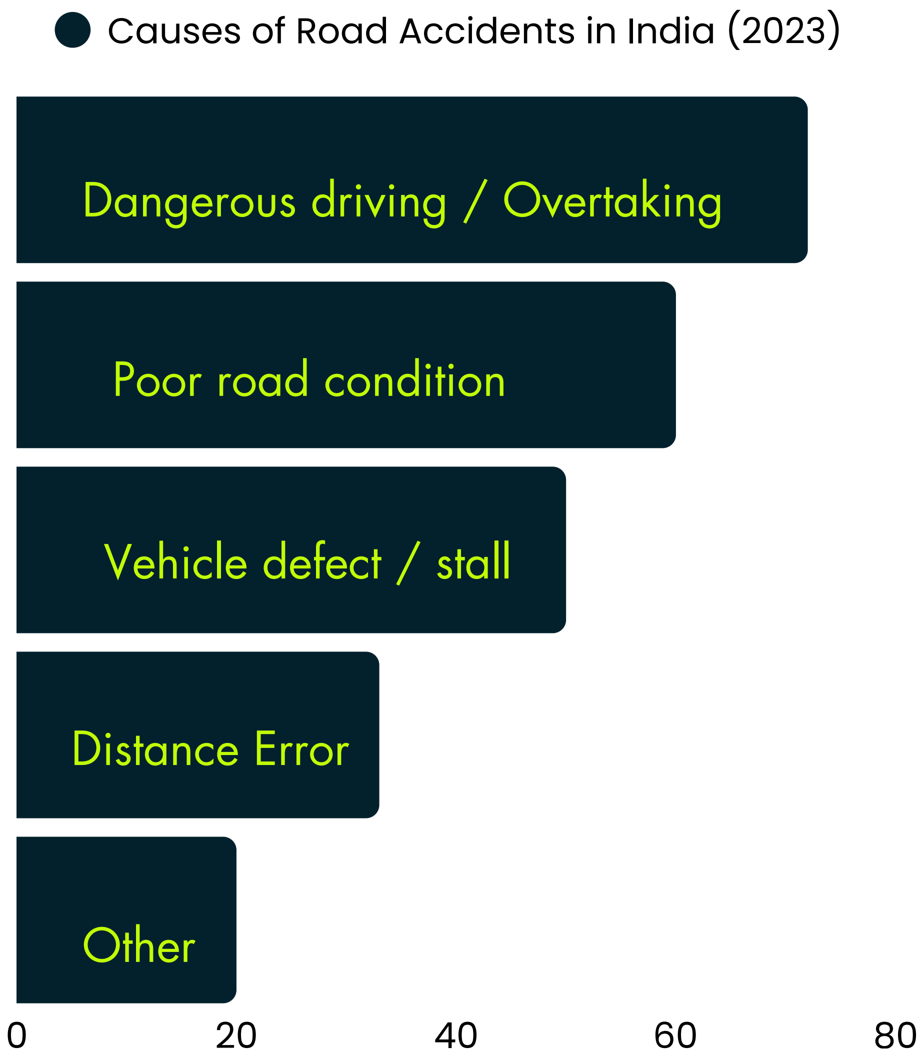
Dashcams capture faces and number plates. Few systems apply on-device **anonymization**, raising privacy concerns.

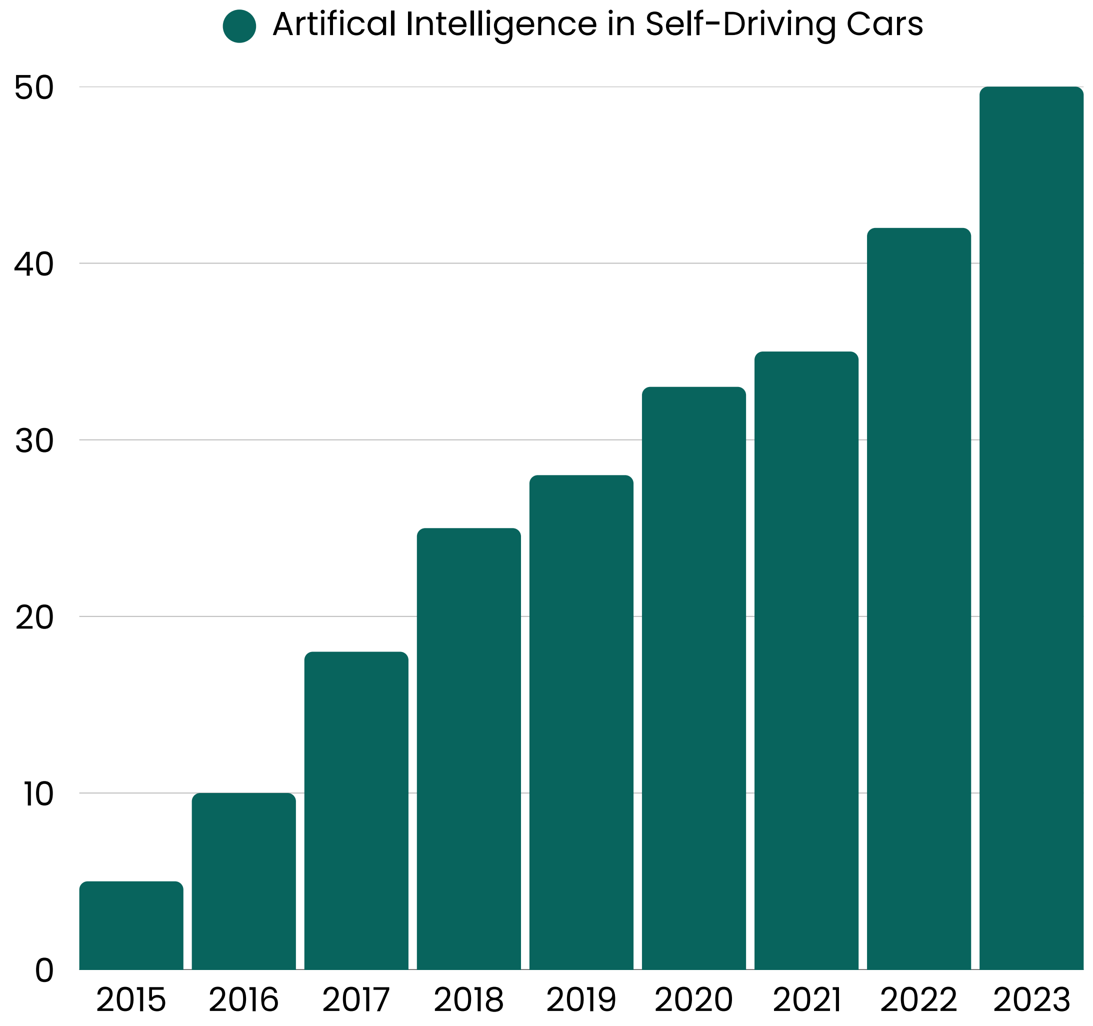
Duplicate Or False Alerts

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

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







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

Companies & their Existing Solutions

Company	Solution Provided By The Company	Where The Solution Falls Short	Our Feature/ USP	How Our Feature Solves the Problem
Tesla	Vision-only Full Self-Driving (FSD) with 8-camera Bird's Eye View (BEV) fusion.	No direct car-to-car communication Delays hazard alerts.	DSRC V2X direct alerts	<100 ms car-to-car alerts
Ford	Cloud-based hazard sharing over C-V2X with limited camera integration.	Cellular latency No unified multi-cam view.	Multi-cam fusion + adaptive frames	Panoramic scene fusion with dynamic frame capture improves detection by ~80% and reduces missed hazards by ~50%
Honda	Honda Sensing with pilot road-condition uploads.	Weak in night/fog scenes.	GAN + Reinforcement Learning(RL)	AI dehazing + RL frame control improves low-visibility detection.
Toyota	Toyota Safety Sense (front cam+radar).	Cannot reliably detect stationary or stalled vehicles beyond front view.	Bounding-box stalled vehicle detection.	Detects stalled vehicles with ~90% precision and <0.5 s latency per frame.
Mercedes-Benz	Car-to-Anything(X) cloud warnings Drive Pilot sensors.	Generates many duplicate alerts Depends on cloud.	Geofenced Notification Engine for Hazard Deduplication.	Geofenced filtering removes redundant alerts, cutting duplicates 70–85% and reducing alert message delivery time.

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.

List Of Features Offered By The Solution

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.

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Process Flow Diagram Or Use-Case Diagram

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Alice enters Source and Destination Locations

Offline Pre-Downloaded Pothole Locations

System calculates multiple routes from the given source and destination

System downloads relevant map tiles and any known hazard locations along those routes

Image Capturing and Processing

The multi-camera unit continuously captures the road scene.

Adaptive Keyframe Sampling

Captures only the most relevant frames by automatically adjusting to scene, motion, and events no duplicates, only what's needed.

The cameras feed a composite image to the on-board AI.

System dehazes the image if the image is hazy

Pothole, unmarked speed bump or debris detected

The AI detects a pothole, unmarked speed breaker or debris which was not present in the predownloaded cloud data.

Stalled Vehicle detected

The AI flags a stalled vehicle

Cloud Update

{
type: pothole/stalled/debris,
lat, lon: GPS location,
severity: 1-5,
confidence: 0-100%,
timestamp,
blurred_crop: base64
}

If the confidence is high , the data of the newly found potholes, speed bumps or debris is updated in the cloud

Geo Fencing

A v2X geo fenced alert using DSRC is sent to nearby vehicles upon detection of potholes, unmarked speed bumps, debris and stalled vehicles avoiding deduplication

Fallback mechanism for low confidence

Fail → Cause → Mitigation

1

FAIL: False positive pothole detection
CAUSE: Shadows/Reflections
MITIGATION: Require Optical-Flow Persistence + IMU bump + Human verification

2

FAIL: V2X spoofing
CAUSE: Malicious Alert Injection
MITIGATION: Sign Messages (PKI) + Trust Score.

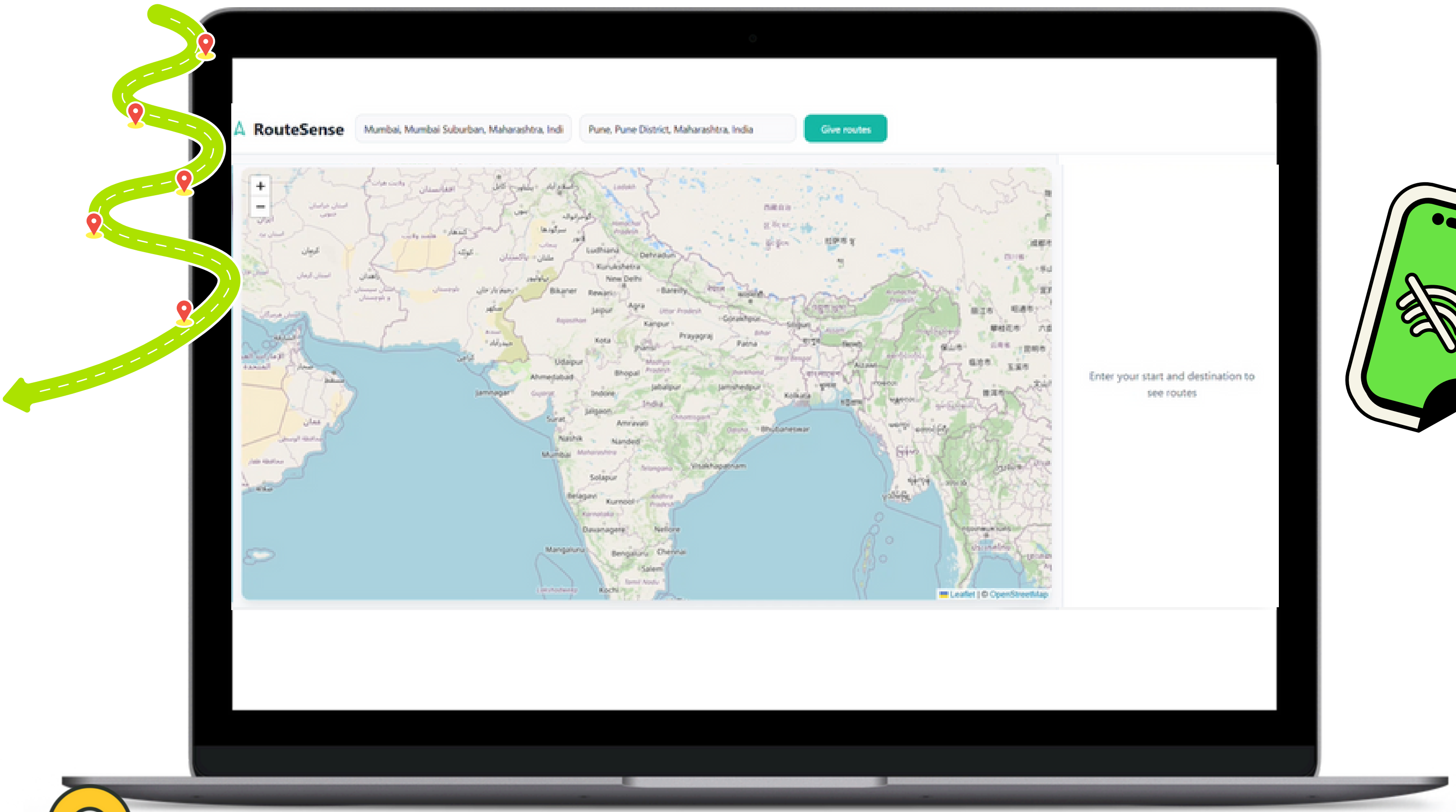
3

FAIL: Low visibility
CAUSE: GAN Hallucination
MITIGATION: Lower-Confidence Gating + Human Verification.

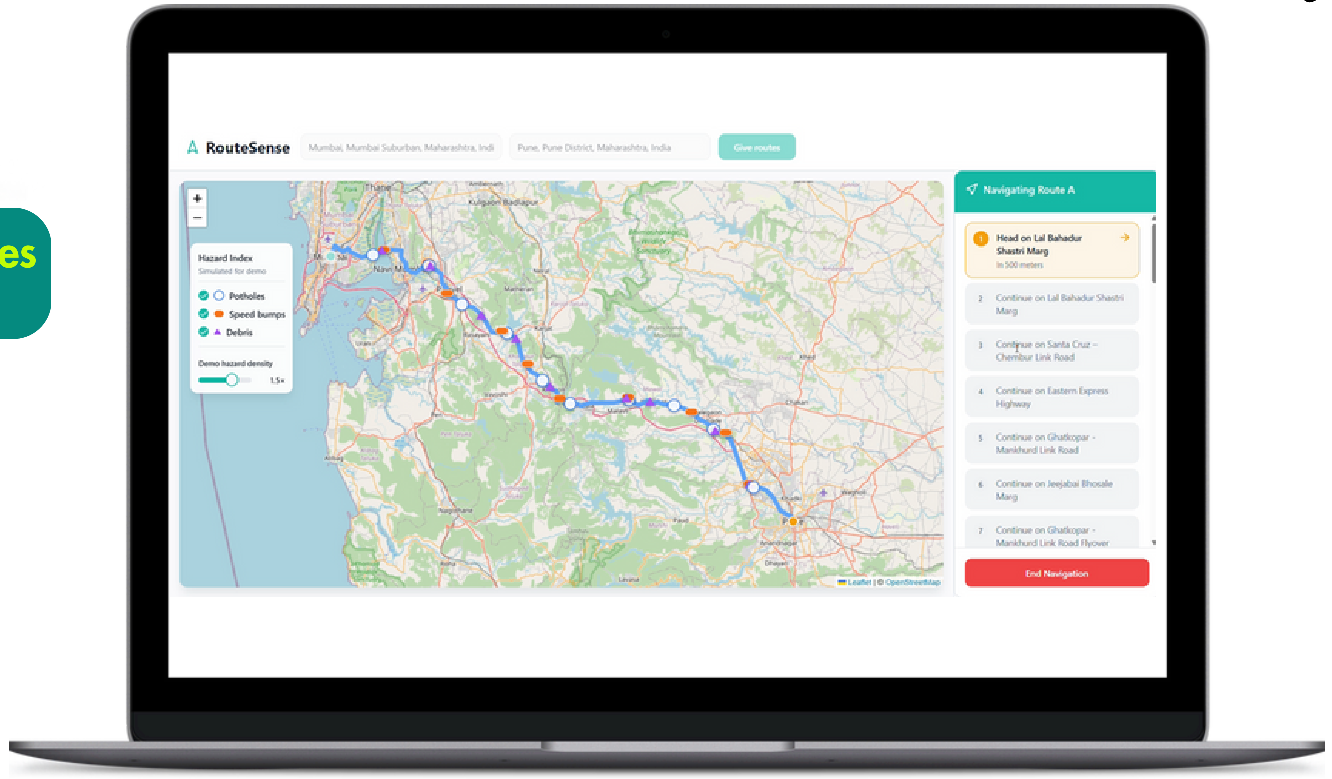
Wherever human verification is required AI asks Alice questions (Voice-Based)

Wireframes/Mock diagrams of the proposed solution

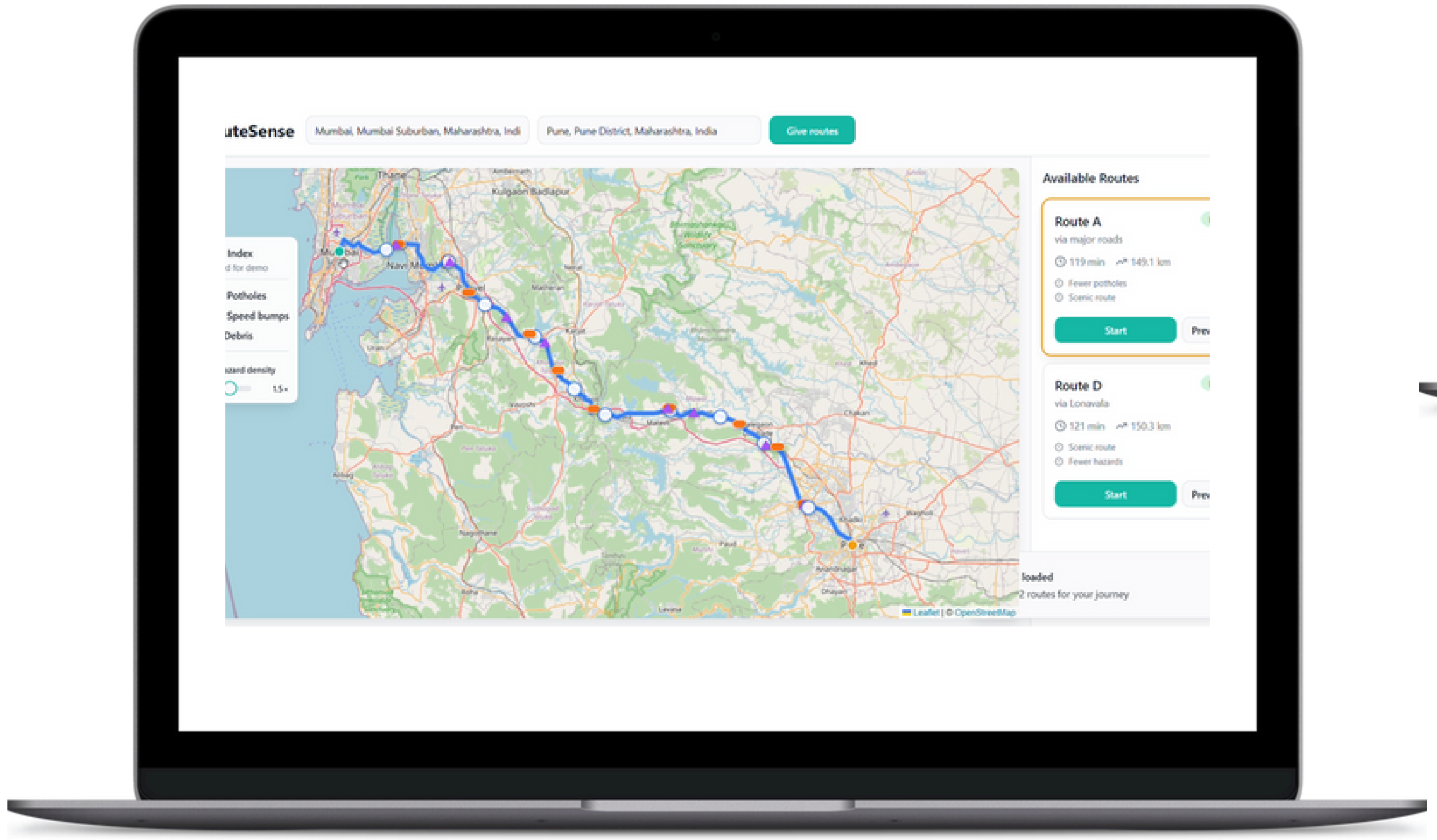
Start & End Location Input: Driver enters source and destination



- Displays potholes, speed bumps, and debris along the path
- Offline support: pre-fetched routes ensure smooth navigation
- Gives real-time voice hazard alerts



Smart Route Fetching: The system fetches the safest and most efficient routes from the preloaded hazard dataset.



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

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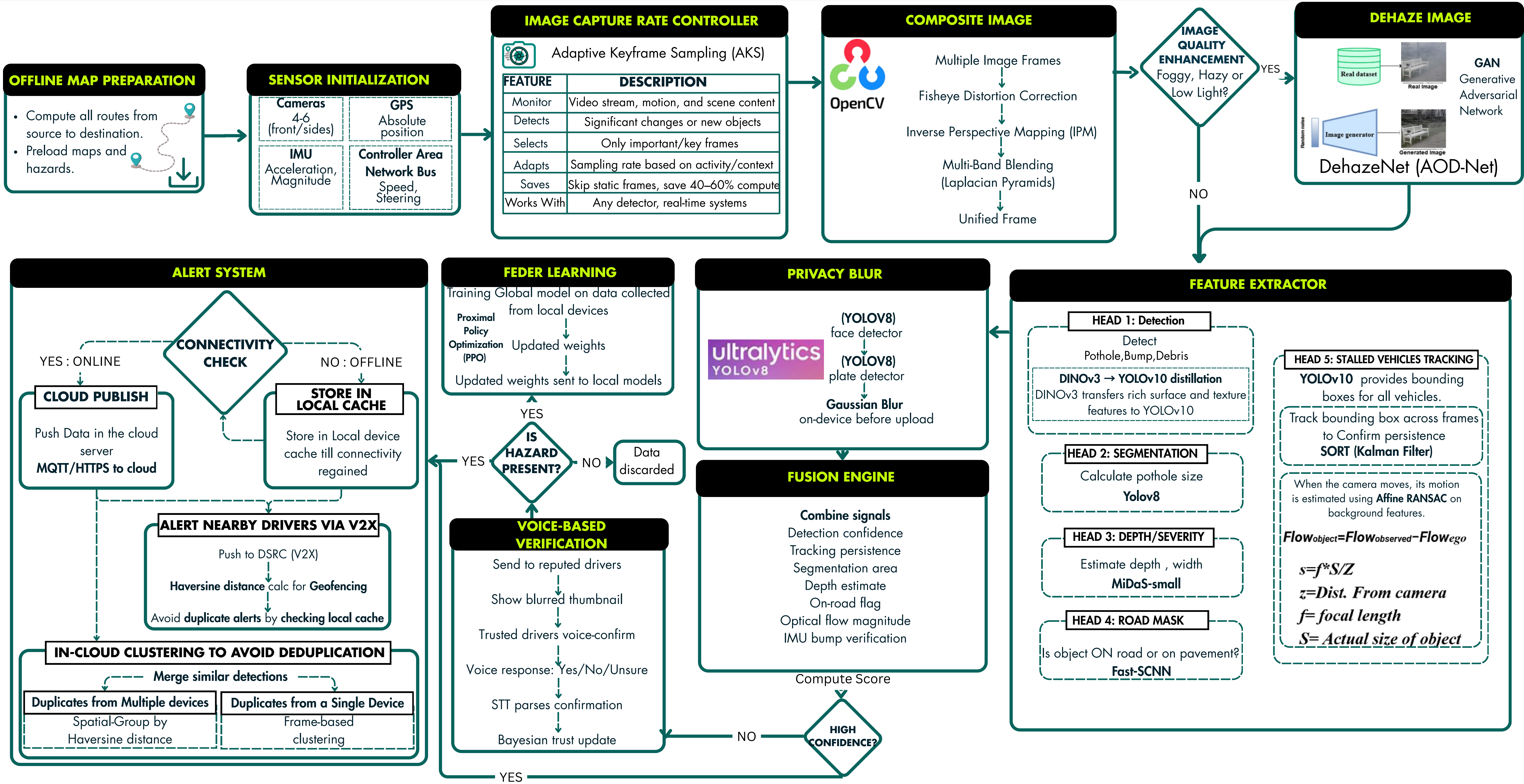

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Technologies To Be Used In The Solution

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MediaPipe
OpenCV
ultralytics YOLOv8
DEIMv2
LLAMA 3
here
Google Translate
CLOUDFLARE
TensorFlow

FRONTEND

User Interface

- Driver App / HMI
- Fleet & City Dashboard
- Offline Mode / Smart Navigation

- User Authentication & Vehicle Binding
- Alert Manager
- Camera Control Panel
- Crowdsourced Map View
- System Health Widget

BACKEND

- API Gateway
- Google Auth, JWT
- Rate Limiter

- Media Processor
- V2X Sync Layer
- FCM

- Geospatial Engine
- Alert Analytics Service
- Federated Model Ops

SECURITY LAYER

- DDOS (CloudFlare)
- Encryption AES

AI-ORIENTED SERVICE

AI Orchestration Layer

- Hazard Detection DINOv3 → YOLOv10 distillation
- Segmentation YoloV8
- Object Tracking (SORT)

- GAN Image Enhancer
- Privacy Blur Model
- Fusion Logic Engine

DATA LAYER

- User DB — Mongo DB
- Media DB — S3
- Telemetry DB — (TimeScale)
- Redis Cache

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Estimated Implementation cost

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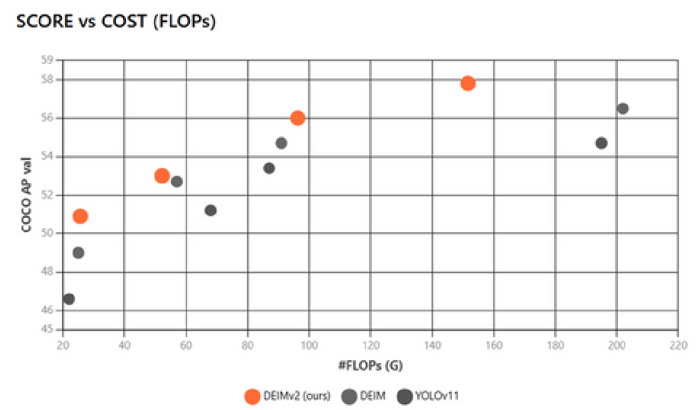
Unit Economics — Per Vehicle / Year

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

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

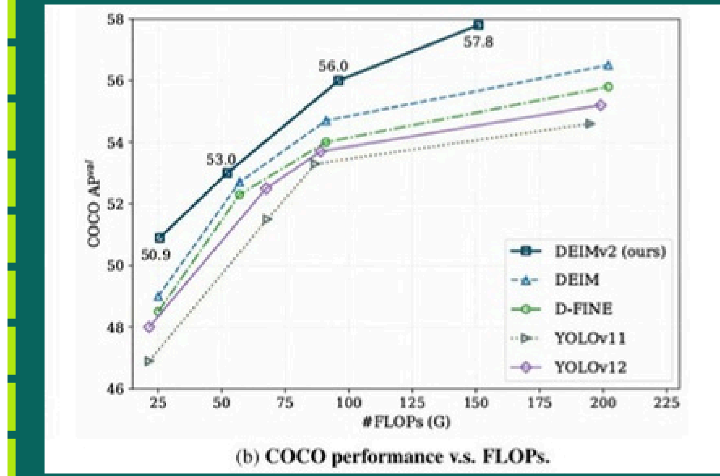


Volkswagen already runs **CARIAD software** on in-car SoCs. We follow the same model software-only, no additional hardware.

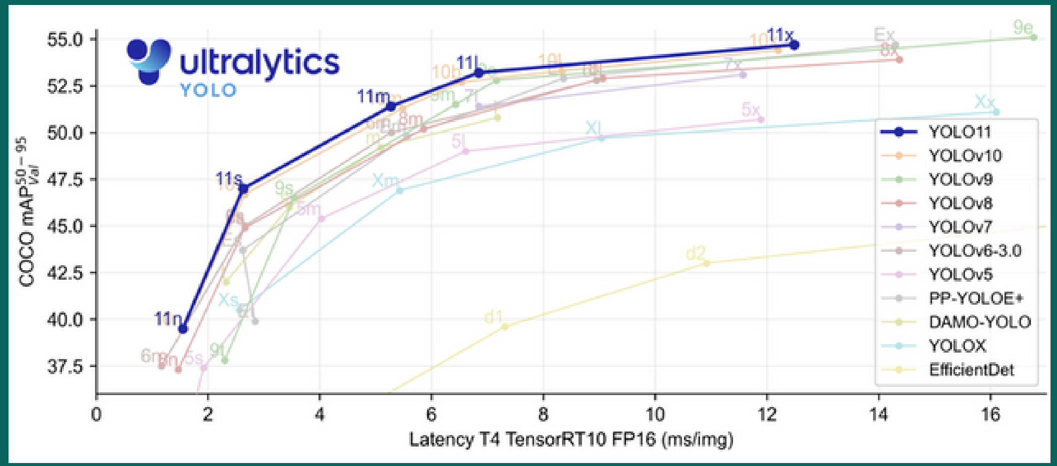
Competitive Cost Benchmark — Annual Per Vehicle

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

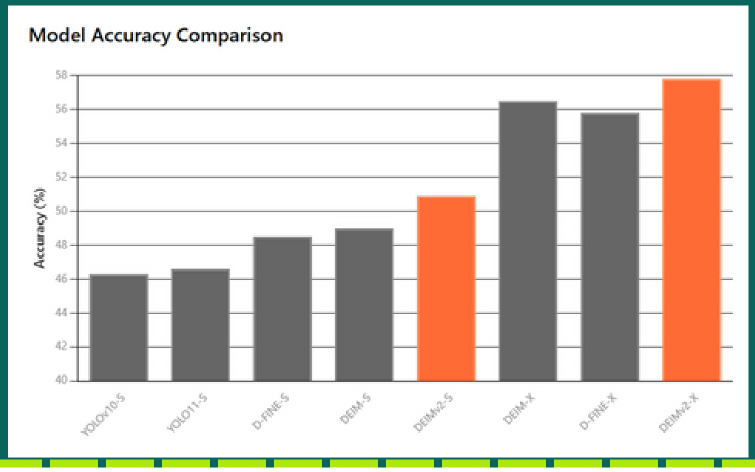


(b) COCO performance v.s. FLOPs.



Metric	YOLOv10	YOLOv10+ DINOv3-S	Comment
mAP (50-95)	47.0	68.1	21.1 percentage point gain
Parameters (M)	9.4	9.7	Same size but more accuracy for same memory
GFLOPs (B)	21.5	24.3	Slightly more compute but smart efficiency DINOv3 & STA modules
Inference Speed (GPU)	2.5 ms	≈ 5.8 ms (but lighter decoder)	Still real time 2× more accuracy per ms
Medium Object Accuracy	51 %	55 %	Better for potholes & debris size objects
Large Object Accuracy	64-65 %	70 %	Catches entire hazards (road blocks / barriers)
Small Object Accuracy	≈ 30 %	31 %	Similar, still okay for distant hazards
Compute Efficiency	-	~ 60 % FLOPs reduction vs comparable DETRs	Faster than other Transformers, practical on vehicle SoCs

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.

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Snapshots of the Prototype

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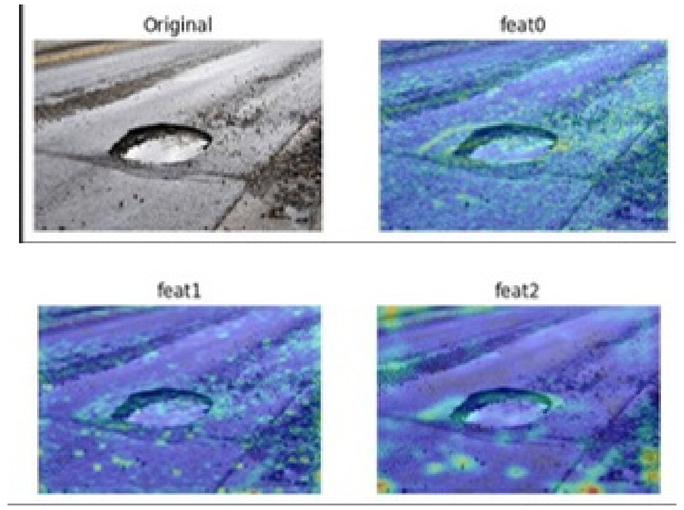
IMAGE CAPTURE RATE CONTROLLER

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

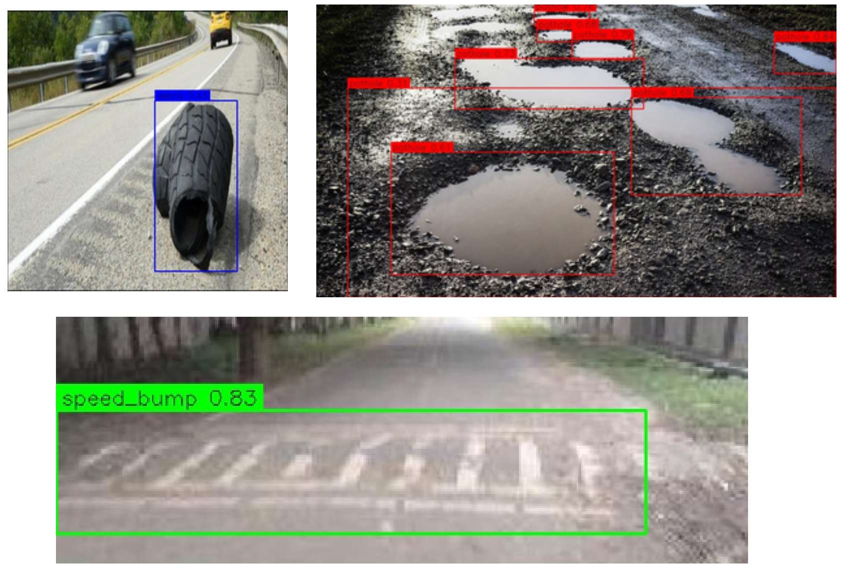


DEHAZE IMAGE

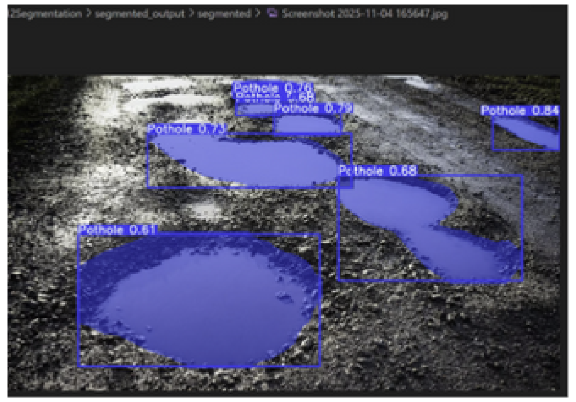
clean = ReLU((x5 * x) - x5 + 1)

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

HEAD 1: DETECTION OF POTHOLE DEBRIES AND BUMPS



HEAD 2: SEGMENTATION



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

Precision: 0.76

Recall: 0.59

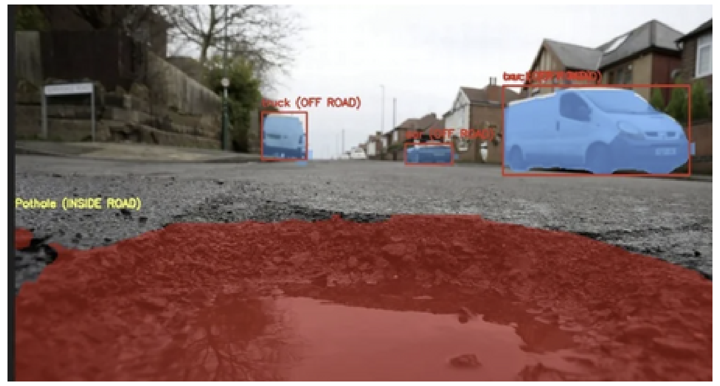
mAP50: 0.72

mAP50–95: 0.45

HEAD 3:DEPTH AND SEVERITY ESTIMATION MODULE

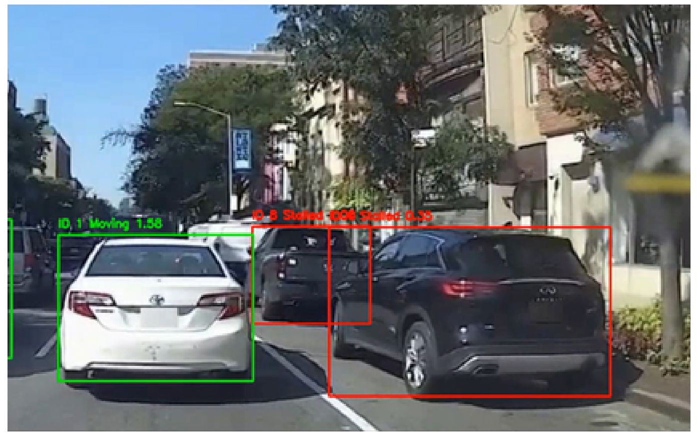
Impact: To accurately estimate each **pothole's depth, width, and area using MiDaS-small,** classify its severity level, and enable real-time, data-driven road maintenance for improved safety and repair prioritization.

HEAD 4: ROAD MASK



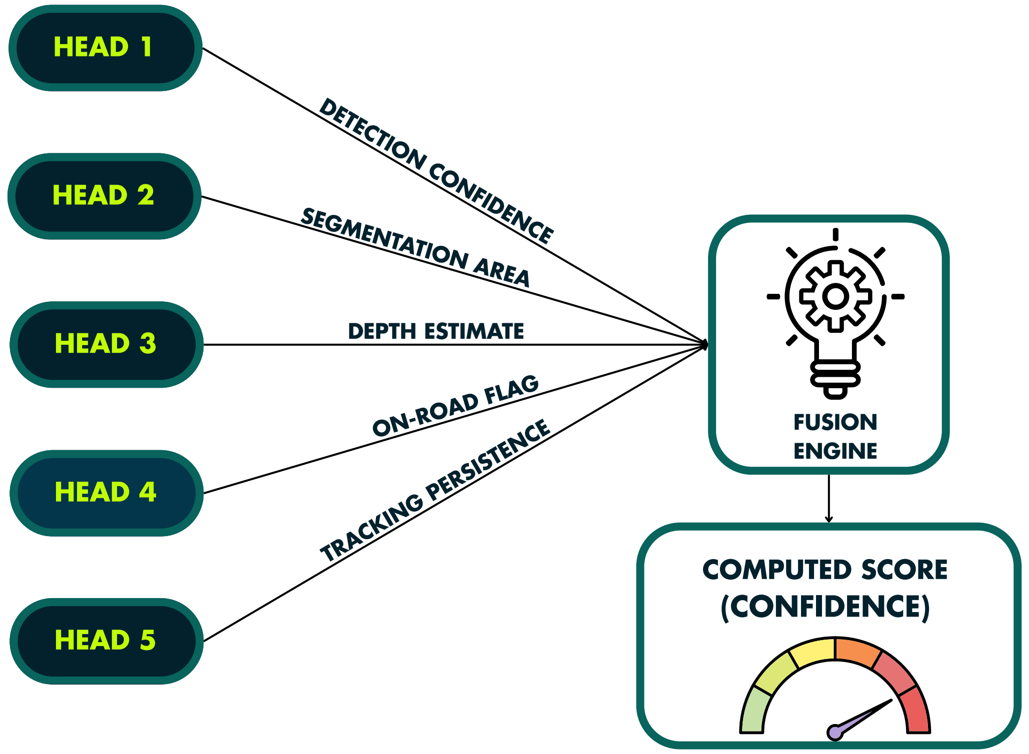
Impact: By integrating **Fast-SCNN** with **YOLO segmentation**, our system intelligently determines whether each detected object : pothole or vehicle lies on the road or pavement, enabling accurate scene understanding for automated safety analytics.

HEAD 5: STALLED VEHICLE



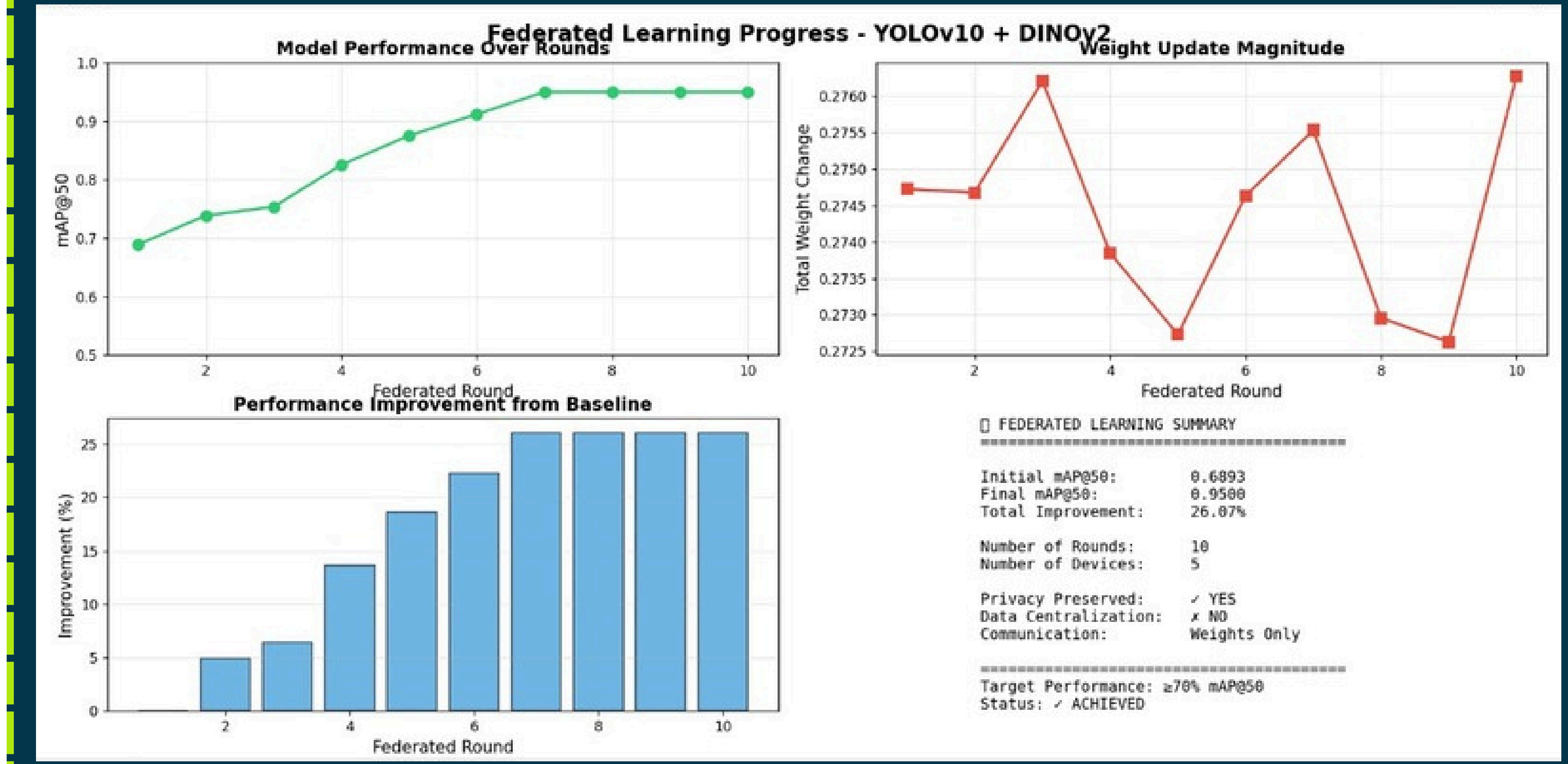
Impact: An AI-based vision system that detects truly s**talled vehicles** by compensating camera motion through **affine RANSAC, EGO motion** and analyzing residual optical flow for persistent low-motion objects.

FUSION ENGINE



Prototype Performance report/Benchmarking

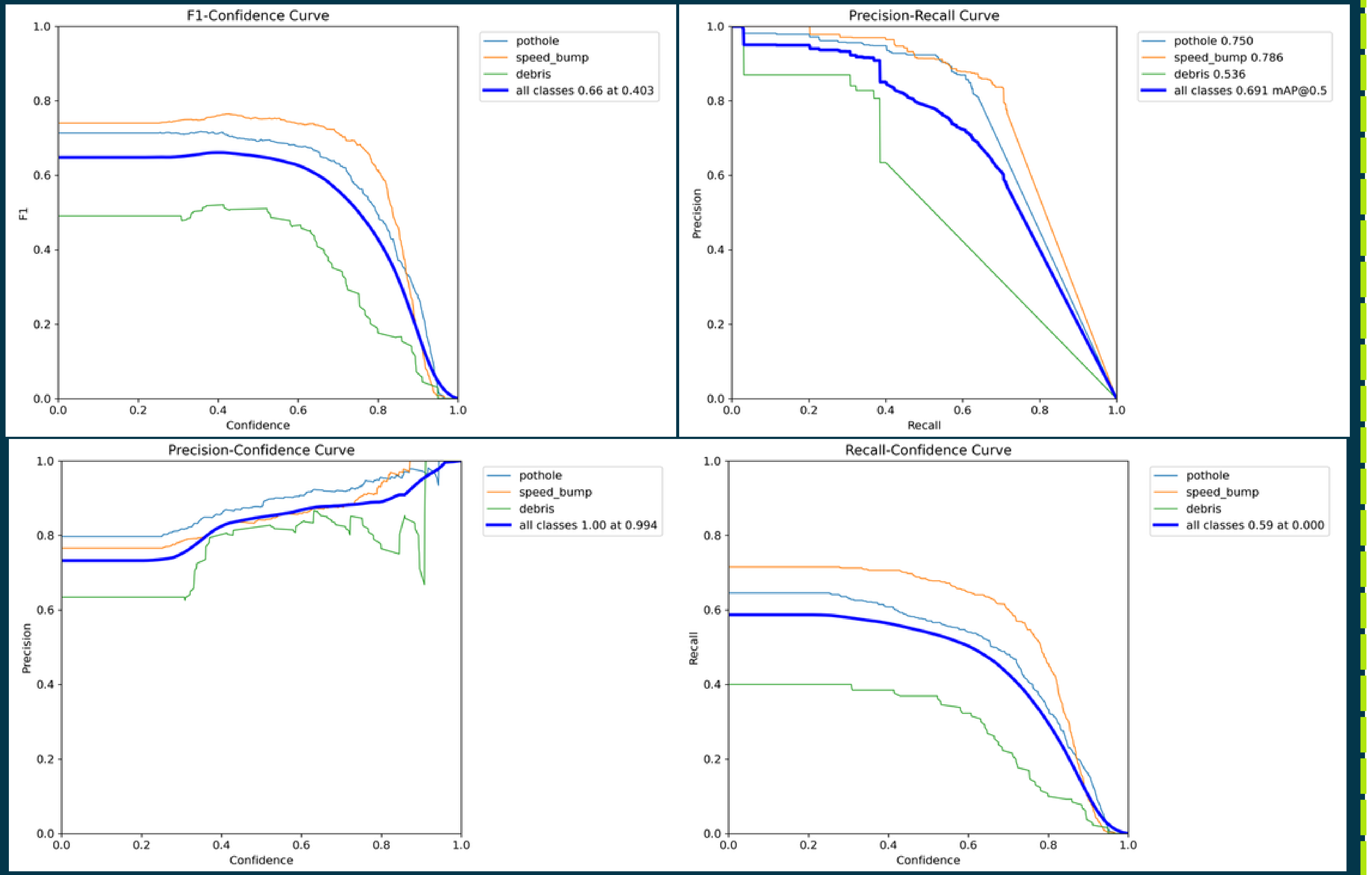
Proximal Policy Optimization(RL Based)



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



Additional Details/Future Development

Challenges	Description
False Positives in Hazard Detection	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.
V2X (DSRC) Communication and Geofencing Errors	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.
Occlusion in High-Traffic Conditions	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.
Detection on Uneven or Patchy Roads	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.
Debris Classification Ambiguity	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.
Environmental Variability	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.
Feedback Loop Stability & Model Drift	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.

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Demo video URL:
https://drive.google.com/drive/folders/1UigdUl6woFvJz7YYPx1ImZYluj1QOAoK?usp=sharing

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

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i.mobilothon 5.0

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