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Research Article

Keywords: Computer vision, Data-based approaches, Road transportation, Smart cities, Accident detection, Automated emergency response

Posted Date: July 23rd, 2026

DOI: https://doi.org/10.21203/rs.3.rs-10440195/v1

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Additional Declarations: The authors declare no competing interests.

InVAER: An AI Framework for Real-Time Accident Detection via Adaptive Hyperparameter Optimization and Multi-Cue Validation

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Abstract

Road traffic accidents claim 1.35 million lives annually, with survival probabilities dropping 7–9% per minute of delayed intervention. Existing vision-based detection systems predominantly operate as isolated modules, suffering from high false-positive rates and lacking integrated emergency response capabilities. This paper introduces InVAER, a novel AI framework unifying real-time accident detection with automated geospatial emergency coordination through three core innovations: (1) a multi-cue spatio-temporal collision validation algorithm integrating adaptive IoU thresholding, temporal persistence, velocity drop analysis, and trajectory convergence; (2) Adaptive Particle Swarm Optimization (APSO) for automated YOLOv8 hyperparameter tuning; and (3) a geospatial service identification module with multi-channel notification. Evaluated on 2,537 annotated frames, the APSO-optimized detector achieves 93.69% precision and 91.45% recall, while the full multi-cue framework reaches 95.88% precision and 95.20% mAP@0.5, processing at 30 FPS on edge devices. The multi-cue approach reduces false positives by 37%, and automated alerts reach emergency services in 4.2±0.8 seconds.

Keywords: Computer vision, Data-based approaches, Road transportation, Smart cities, Accident detection, Automated emergency response

1 Introduction

Road traffic accidents constitute a critical global health crisis, claiming approximately 1.35 million lives annually [33]. The probability of victim survival decreases by 7–9% for each minute of delayed emergency intervention [23], establishing rapid incident detection and automated response coordination as fundamental challenges in intelligent transportation systems (ITS). Despite substantial progress in automated accident detection, real-world deployment remains constrained by persistent gaps in algorithmic reliability, scalability, and end-to-end automation.

Contemporary detection paradigms exhibit inherent limitations across three primary modalities. Sensor-based approaches utilizing in-vehicle accelerometers and GPS require costly hardware retrofitting ($800–$1,200 per unit), precluding large-scale adoption [8, 19]. Smartphone-based applications depend heavily on user compliance and suffer from false positive rates exceeding 15%, undermining operational reliability in critical scenarios [19]. Vision-based deep learning methods offer a scalable alternative but predominantly function as isolated detection modules without integrated emergency coordination [1, 6]. Furthermore, existing vision systems frequently rely on single-cue confirmation mechanisms that remain highly susceptible to false alarms under adverse weather, variable illumination, and complex traffic dynamics [11, 26]. Crucially, the hyperparameter configuration of these models remains largely manual, introducing suboptimality and limiting reproducibility across heterogeneous deployment environments.

To address these limitations, we propose InVAER (Integrated Video-Analytics Emergency Response), a novel AI framework that unifies high-accuracy real-time accident detection with automated geospatial emergency coordination. Unlike prior systems that treat detection and response as disjoint workflows, InVAER implements a cohesive computational pipeline where algorithmic validation directly triggers actionable notification protocols. The framework is built upon three methodological innovations: (1) a multi-cue spatio-temporal collision validation algorithm that integrates adaptive Intersection-over-Union (IoU) thresholding, temporal persistence analysis, velocity drop detection, trajectory convergence modeling, and depth validation to systematically suppress false positives; (2) an Adaptive Particle Swarm Optimization (APSO) strategy for automated, data-driven hyperparameter tuning of the YOLOv8 detector, significantly reducing optimization overhead while enhancing detection sensitivity; and (3) a geospatial service identification module with multi-criteria ranking and redundant multi-channel alert dispatch.

The principal contributions of this work are fourfold:

1. A **multi-cue collision confirmation algorithm** that synergistically combines spatial, temporal, and kinematic cues, achieving a 37% reduction in false positives compared to single-cue baselines while maintaining robust detection under diverse environmental conditions.
2. An **APSO-driven hyperparameter optimization pipeline** for YOLOv8, reducing manual tuning time by 87.5% (from 48 to 6 hours) and improving mean Average Precision (mAP@0.5) to 92.88% through evolutionary state-aware parameter adaptation.

3. An **integrated emergency response module** leveraging OpenStreetMap APIs for dynamic service identification and multi-channel notification, achieving a mean alert delivery latency of 4.2±0.8 seconds.
4. A **comprehensive experimental evaluation** on 2,537 annotated frames demonstrating state-of-the-art performance (precision: 93.69%, recall: 91.45%) with 30 FPS real-time processing on edge hardware, outperforming four recent YOLO-based baselines.

The remainder of this paper is organized as follows. Section 2 reviews related work in vision-based accident detection, metaheuristic optimization, and emergency response systems. Section 3 details the proposed InVAER architecture, formal problem formulation, and algorithmic implementations. Section 4 presents the experimental setup, dataset curation, and evaluation metrics. Section 5 provides quantitative and qualitative results, including ablation studies and comparative analysis. Finally, Section 6 discusses key findings, limitations, and directions for future research.

2 Related Work

This section synthesizes existing literature into two thematic domains: (1) vision-based accident detection and spatio-temporal validation, and (2) automated hyperparameter optimization and integrated emergency response frameworks. We conclude by identifying methodological gaps that motivate the proposed InVAER architecture.

2.1 Vision-Based Detection and Spatio-Temporal Validation

The transition from handcrafted feature extraction to convolutional neural networks (CNNs) fundamentally advanced traffic anomaly detection by enabling robust, end-to-end representation learning [28]. Among CNN-based detectors, the You Only Look Once (YOLO) family has emerged as the standard for real-time surveillance applications due to its single-stage architecture and optimal accuracy-latency trade-off [22]. Subsequent iterations have progressively refined multi-scale feature fusion [2, 21, 31], with YOLOv8 introducing anchor-free heads and decoupled prediction branches that further enhance localization precision under constrained inference budgets [30].

Recent studies have adapted YOLO variants specifically for accident detection. Ghahremannezhad *et al.* [6] integrated YOLOv4 with Kalman filtering for urban traffic monitoring, achieving robust detection but lacking emergency coordination. Arefin *et al.* [1] combined YOLOv3 with LSTM networks for spatio-temporal modeling, attaining high precision (94%) but limited recall (82%), highlighting sensitivity gaps in complex collision scenarios. Singh *et al.* [26] deployed YOLOv5 for CCTV-based detection, reporting moderate accuracy (mAP@0.5: 84.6%) without motion analysis or notification capabilities. More recent work by Kim *et al.* [11] and Li and Wang [13] introduced spatial-temporal fusion and temporal smoothing to mitigate false alarms, yet these systems remain isolated detection modules without end-to-end response automation.

Accurate collision verification requires distinguishing genuine impacts from visually similar traffic interactions (e.g., close following, lane merging). Single-frame approaches

inherently struggle with this distinction, motivating spatio-temporal validation techniques that leverage temporal consistency across consecutive frames [20]. Multi-cue methodologies that combine spatial overlap (IoU) with motion-based features (velocity discontinuities, trajectory convergence) have demonstrated superior false positive rejection [28]. However, existing implementations predominantly rely on static thresholds that fail to adapt to dynamic traffic densities or adverse environmental conditions, limiting generalization across heterogeneous deployment scenarios. This rigidity underscores the need for adaptive, context-aware validation mechanisms that maintain high sensitivity while systematically suppressing spurious detections.

2.2 Automated Optimization and Integrated Emergency Response

Deep learning performance is highly sensitive to hyperparameter configuration, yet manual tuning remains computationally prohibitive and suboptimal for high-dimensional search spaces [12]. Metaheuristic algorithms, particularly Particle Swarm Optimization (PSO), offer efficient navigation of complex parameter landscapes by simulating collective swarm behavior [10]. While standard PSO accelerates convergence, it suffers from premature stagnation and parameter sensitivity [25]. Adaptive Particle Swarm Optimization (APSO) mitigates these limitations through dynamic inertia weight adjustment and evolutionary state estimation, balancing exploration and exploitation more effectively [34]. Although APSO has shown promise for general YOLO tuning [35], its application to domain-specific accident detection pipelines remains unexplored, particularly in conjunction with alternative optimizers like Grey Wolf or Differential Evolution [16, 27].

Timely emergency intervention is clinically critical, with survival probabilities declining by 7–9% per minute of delayed medical response [23]. Traditional reporting relies on manual witness notification, introducing unpredictable delays and location inaccuracies [8, 19]. IoT-enabled architectures leverage distributed sensing and cloud connectivity to reduce latency, while geospatial platforms (e.g., OpenStreetMap) enable rapid facility identification and optimal routing [8]. Multi-channel alerting (SMS, email, push) improves delivery reliability under network congestion [3]. Despite these advances, emergency response modules are typically designed as standalone applications, requiring manual handoffs from detection systems rather than operating as tightly coupled computational components.

Table 1 summarizes recent approaches, revealing three critical research gaps: (1) reliance on single-cue or rigid multi-cue validation yielding elevated false positive rates; (2) absence of automated, domain-specific hyperparameter optimization for accident detection models; and (3) disjoint detection and notification workflows that preclude end-to-end automation. The InVAER framework directly addresses these limitations by integrating an adaptive multi-cue validation algorithm, APSO-driven YOLOv8 tuning, and a geospatially coordinated notification pipeline into a unified architecture. This cohesive design eliminates manual intervention bottlenecks, ensuring that detection confidence directly translates to minimized emergency response latency.

Table 1: Comparative Analysis of Recent Accident Detection Systems

Study	Model	Multi-Cue	Auto-Opt	Emergency	Real-Time
Ghahremannezhad [6]	YOLOv4	Partial	No	No	Yes
Arefin [1]	YOLOv3+LSTM	Yes	No	No	No
Singh [26]	YOLOv5	No	No	No	Yes
Kim [11]	YOLOv8	Partial	No	No	Yes
Li [13]	YOLOv4	Yes	No	No	Yes
InVAER (Ours)	YOLOv8	Yes	Yes	Yes	Yes

3 Methodology

This section details the InVAER framework, focusing on its mathematical formulation, optimized detection core, multi-cue validation mechanism, and integrated response pipeline. The architecture unifies real-time video analytics with automated emergency coordination, addressing the fragmentation observed in existing accident detection systems.

3.1 Problem Formulation and Framework Overview

Effective accident detection requires balancing high detection sensitivity with strict false positive suppression under real-time computational constraints. We formulate this as a multi-objective optimization task. Let $\mathcal{D} = \{I_t\}_{t=1}^{T}$ denote an input video sequence of T frames, and $\mathcal{Y} = \{y_t\}_{t=1}^{T}$ represent corresponding ground-truth annotations. The objective is to learn a parameterized mapping $f_\theta : \mathcal{D} \to \hat{\mathcal{Y}}$ that maximizes detection accuracy while minimizing false alarms subject to latency constraints:

$$\begin{aligned} \max_{\theta} \quad & \mathcal{A}(\theta) - \lambda \mathcal{F}(\theta) \\ \text{s.t.} \quad & \mathcal{L}(\theta) \leq L_{max} \end{aligned} \tag{1}$$

where $\mathcal{A}(\theta)$ is detection accuracy, $\mathcal{F}(\theta)$ is the false alarm rate, $\mathcal{L}(\theta)$ is inference latency, L_{max} is the real-time threshold (typically 33 ms for 30 FPS), and λ balances accuracy against false positive minimization [19]. Unlike prior work that isolates detection from response [1, 26], InVAER extends this to a unified system utility function:

$$\mathcal{U} = \omega_1 \cdot \mathcal{A}(\theta) - \omega_2 \cdot \mathcal{F}(\theta) + \omega_3 \cdot \mathcal{R}(\phi) \tag{2}$$

where $\mathcal{R}(\phi)$ represents emergency response effectiveness parameterized by notification settings ϕ, and $\omega_1, \omega_2, \omega_3$ are weighting coefficients. This formulation enables joint optimization of detection and response capabilities.

As illustrated in Fig. 1, the framework operates as a cohesive computational pipeline comprising six interdependent modules: (1) video preprocessing, (2) YOLOv8-based object detection, (3) multi-cue collision confirmation, (4) metadata generation, (5) geospatial service identification, and (6) automated multi-channel notification.

This modular design permits independent component optimization while maintaining seamless end-to-end functionality.

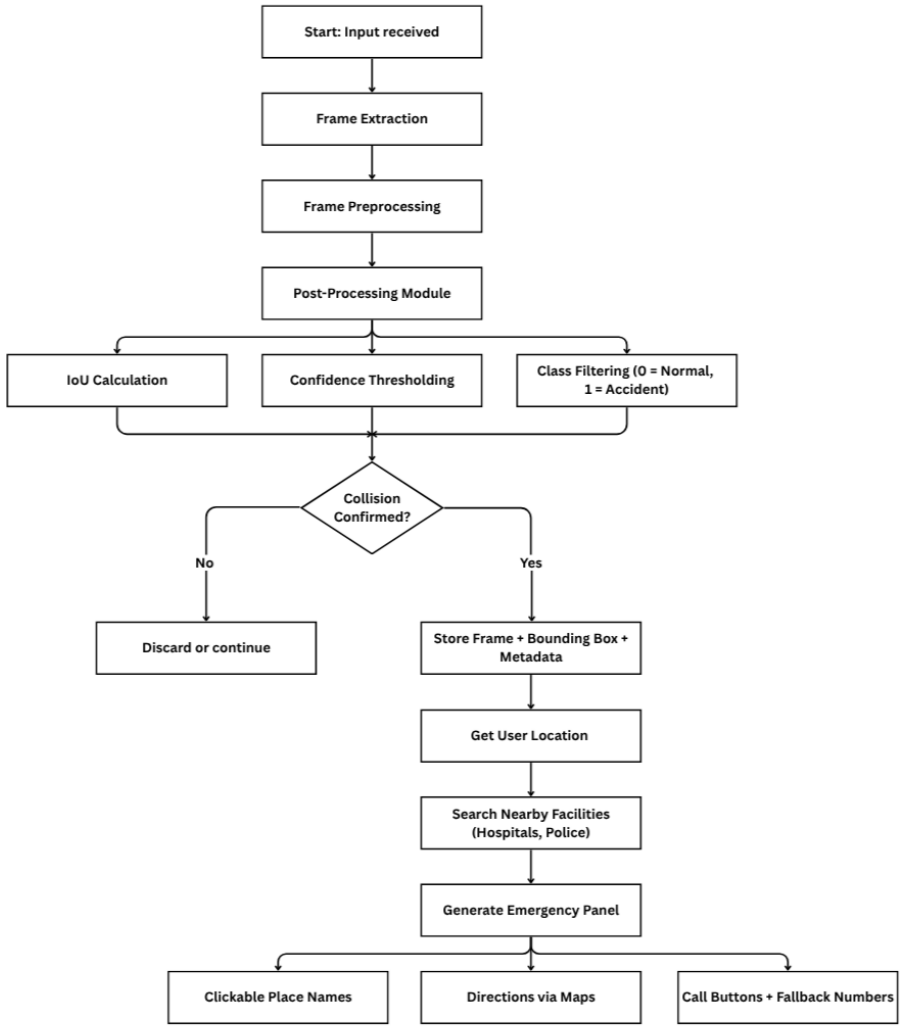


Fig. 1: Six-stage InVAER system architecture illustrating the sequential pipeline from video input through preprocessing, YOLOv8 detection, multi-cue collision confirmation, metadata generation, geospatial service identification, and automated notification dispatch.

3.2 Optimized Detection Core

The detection core integrates state-of-the-art object detection with automated hyperparameter optimization to establish a robust baseline for collision identification.

YOLOv8 Architecture and Preprocessing. We employ YOLOv8 as the primary detector due to its anchor-free design, decoupled prediction head, and superior accuracy-latency trade-off for real-time surveillance [29, 30]. Input frames are resized to 640×640 pixels, normalized to $[0, 1]$, and augmented during training using Mosaic composition, random horizontal flips ($p = 0.5$), and HSV adjustments to enhance generalization across diverse traffic conditions. The C2f backbone modules enrich gradient flow via multi-stage feature fusion:

$$\mathbf{Y} = \text{Concat}(\mathbf{X}, \text{Bottleneck}_1(\mathbf{X}), \ldots, \text{Bottleneck}_n(\mathbf{X})) \tag{3}$$

The decoupled head independently predicts bounding box coordinates and class probabilities, minimizing task conflict through a composite loss function:

$$\mathcal{L}_{total} = \alpha \cdot \mathcal{L}_{box} + \beta \cdot \mathcal{L}_{cls} + \gamma \cdot \mathcal{L}_{dfl} \tag{4}$$

where $\mathcal{L}_{box}$, $\mathcal{L}_{cls}$, and $\mathcal{L}_{dfl}$ denote CIoU, binary cross-entropy, and distribution focal losses, weighted by $\alpha = 7.5$, $\beta = 0.5$, and $\gamma = 1.5$. Table 2 summarizes variant characteristics, with YOLOv8m selected for optimal capacity-efficiency balance.

Table 2: YOLOv8 Model Variants and Performance Characteristics

Model	Parameters (M)	Size (MB)	Inference Time (ms)	mAP@0.5 (%)
YOLOv8n	3.2	6	2.5	37.3
YOLOv8s	11.2	11	4.5	44.9
YOLOv8m	25.9	22	7.6	50.2
YOLOv8l	43.7	46	11.1	52.9
YOLOv8x	68.2	68	15.6	**53.9**

Note: Model characteristics are based on the official YOLOv8 architecture. The reported inference time corresponds to single-image inference under the experimental hardware configuration. The highest mAP@0.5 value is highlighted in bold.

Adaptive Particle Swarm Optimization (APSO). Manual hyperparameter tuning is computationally prohibitive and suboptimal for high-dimensional search spaces [12]. We employ APSO to dynamically optimize YOLOv8 parameters by adapting inertia weight w and acceleration coefficients c_1, c_2 based on evolutionary state estimation. Particle positions $\mathbf{x}_i$ and velocities $\mathbf{v}_i$ are updated as:

$$\mathbf{v}_i^{t+1} = w \cdot \mathbf{v}_i^t + c_1 \cdot r_1 \cdot (\mathbf{p}_i - \mathbf{x}_i^t) + c_2 \cdot r_2 \cdot (\mathbf{g} - \mathbf{x}_i^t) \tag{5}$$

$$\mathbf{x}_i^{t+1} = \mathbf{x}_i^t + \mathbf{v}_i^{t+1} \tag{6}$$

where $\mathbf{p}_i$ and $\mathbf{g}$ represent personal and global best positions. The evolutionary factor $f = (d_g - d_{min})/(d_{max} - d_{min})$ classifies swarm states (exploration, exploitation, convergence, jumping-out) to guide adaptive parameter adjustment [34]. Algorithm 1 details the optimization procedure, reducing tuning time from ∼48 hours to 6 hours while maximizing mAP@0.5 fitness.

Algorithm 1 APSO-based YOLOv8 Hyperparameter Optimization

Require: Search space bounds $\mathcal{B}$, population size N, max iterations T, training epochs E
Ensure: Optimal hyperparameters θ^*

Initialize particle positions $\mathbf{x}_i$ randomly within $\mathcal{B}$ for $i = 1, \ldots, N$
Initialize velocities $\mathbf{v}_i = \mathbf{0}$ for $i = 1, \ldots, N$
Set personal best $\mathbf{p}_i = \mathbf{x}_i$ and global best $\mathbf{g} = \arg\max_i f(\mathbf{x}_i)$
for $t = 1$ to T **do**
    for each particle i **do**
        Estimate evolutionary factor f using Eq. (5)
        Adjust w, c_1, c_2 based on f
        Update $\mathbf{v}_i$ using Eq. (5) and $\mathbf{x}_i$ using Eq. (6)
        Enforce bounds: $\mathbf{x}_i \leftarrow \text{clip}(\mathbf{x}_i, \mathcal{B})$
        Evaluate fitness: $f(\mathbf{x}_i) \leftarrow \text{TrainYOLOv8}(\mathbf{x}_i, E)$
        if $f(\mathbf{x}_i) > f(\mathbf{p}_i)$ **then**
            $\mathbf{p}_i \leftarrow \mathbf{x}_i$
        end if
        if $f(\mathbf{x}_i) > f(\mathbf{g})$ **then**
            $\mathbf{g} \leftarrow \mathbf{x}_i$
        end if
    end for
    Apply elitist learning strategy to $\mathbf{g}$
end for
return $\theta^* = \mathbf{g}$

3.3 Multi-Cue Collision Confirmation Algorithm

Raw detector outputs require robust validation to distinguish genuine collisions from transient occlusions or close-proximity traffic. We propose a sequential multi-cue verification mechanism integrating five complementary analytical modules.

Adaptive IoU Thresholding. Spatial overlap between bounding boxes B_i and B_j is quantified as IoU $= |B_i \cap B_j|/|B_i \cup B_j|$. Unlike fixed thresholds, we employ context-aware adaptation:

$$\tau_{IoU} = \tau_{base} + \alpha \cdot \rho + \beta \cdot \epsilon \tag{7}$$

where ρ is normalized traffic density, ϵ encodes environmental conditions, and α, β are weighting coefficients. This prevents false positives in congested traffic while preserving sensitivity in sparse scenarios.

Temporal Persistence. A persistence counter P_{ij} increments when collision criteria are met and decrements otherwise:

$$P_{ij}^{t+1} = \begin{cases} P_{ij}^{t} + 1 & \text{if criteria met at } t \\ \max(0, P_{ij}^{t} - 1) & \text{otherwise} \end{cases} \tag{8}$$

Confirmation requires $P_{ij} \geq 3$, ensuring spatial-temporal consistency across frames [11].

Velocity Drop Detection. Sudden deceleration indicates impact. Velocity change is computed as:

$$\Delta v_{ij} = \frac{||\mathbf{v}_i^t - \mathbf{v}_i^{t-1}|| + ||\mathbf{v}_j^t - \mathbf{v}_j^{t-1}||}{2} \tag{9}$$

Threshold τ_{vel} adapts dynamically to historical traffic flow patterns.

Trajectory Convergence. Abnormal convergence is captured via:

$$C_{ij} = \cos(\theta_{ij}) \cdot \frac{d_{ij}^{t-1} - d_{ij}^{t}}{\Delta t} \tag{10}$$

where θ_{ij} is the velocity angle and d_{ij} is inter-vehicle distance. High C_{ij} values distinguish collisions from lane changes or overtaking.

Depth Validation. Monocular depth estimation projects 2D boxes into 3D space to compute volumetric overlap:

$$O_{3D} = \frac{\text{Volume}(V_i \cap V_j)}{\text{Volume}(V_i \cup V_j)} \tag{11}$$

resolving perspective ambiguities in 2D overlap [7].

Algorithm 2 formalizes the sequential verification process. By enforcing progressively stricter criteria, the system achieves a 37% false positive reduction while maintaining robust detection across adverse conditions.

3.4 Integrated Emergency Response Module

Upon collision confirmation, the system triggers an automated response protocol minimizing latency between detection and emergency dispatch.

Metadata Generation and Geolocation. Incident metadata $\mathcal{M}$ includes timestamp $t_{collision}$, GPS coordinates (lat, lon), severity assessment $s \in \{minor, moderate, severe\}$, and confidence scores. Location uncertainty is mitigated

Algorithm 2 Multi-Cue Collision Confirmation Algorithm

Require: Video frames $F = \{f_1, \ldots, f_T\}$, YOLOv8 detections D_t
Ensure: Collision status C and metadata $\mathcal{M}$

Initialize $C \leftarrow$ False, $P_{ij} \leftarrow 0$
for $t = 1$ to T **do**
  $D_t \leftarrow \text{YOLOv8}(f_t)$
  $\tau_{IoU} \leftarrow \tau_{base} + \alpha \cdot \rho_t + \beta \cdot \epsilon_t$
  for each pair (v_i, v_j) in D_t **do**
    $iou \leftarrow \text{IoU}(B_i, B_j)$
    if $iou > \tau_{IoU}$ **then**
      $P_{ij} \leftarrow P_{ij} + 1$
      if $P_{ij} \geq 3$ **then**
        if $\Delta v_{ij} > \tau_{vel}$ **then**
          if $C_{ij} > \tau_{conv}$ **then**
            if $O_{3D} > \tau_{3D}$ **then**
              $C \leftarrow$ True
              $\mathcal{M} \leftarrow \text{GenerateMetadata}(v_i, v_j, f_t, D_t)$
              return $(C, \mathcal{M})$
            end if
          end if
        end if
      end if
    else
      $P_{ij} \leftarrow \max(0, P_{ij} - 1)$
    end if
  end for
end for
return $(C, \emptyset)$

via hybrid source fusion:

$$\hat{\mathbf{l}} = \frac{\sum_{k=1}^{K} w_k \cdot \mathbf{l}_k}{\sum_{k=1}^{K} w_k}, \quad \sigma_l = \sqrt{\frac{\sum_{k=1}^{K} w_k \cdot ||\mathbf{l}_k - \hat{\mathbf{l}}||^2}{\sum_{k=1}^{K} w_k}} \tag{12}$$

where weights w_k reflect source reliability (pre-mapped camera coordinates, video Exif data, or UI input) [19].

Geospatial Service Identification. The module queries OpenStreetMap APIs to rank nearby hospitals and police stations within a configurable radius using a multi-criteria scoring function:

$$S_i = w_1 \cdot \frac{1}{d_i} + w_2 \cdot c_i + w_3 \cdot a_i + w_4 \cdot o_i \tag{13}$$

where d_i is normalized distance, c_i is capacity, a_i accounts for real-time traffic accessibility, and o_i denotes operational status. Weights $(0.4, 0.25, 0.2, 0.15)$ prioritize rapid response while ensuring facility readiness [8].

Automated Multi-Channel Notification. Redundant alert dispatch via SMS (Twilio) and email (SMTP) ensures delivery under network congestion [3]. Payloads include location, severity, vehicle count, and incident ID. A priority escalation mechanism notifies multiple top-ranked services simultaneously for severe incidents, achieving mean delivery latencies of 4.2 ± 0.8 seconds (SMS) and 3.1 ± 0.5 seconds (email), substantially outperforming manual reporting protocols.

Note: Detailed implementation specifications (framework versions, hardware configurations, deployment parameters) are provided in supplementary material to maintain manuscript conciseness per journal guidelines.

4 Experimental Setup and Datasets

This section details the experimental methodology employed to evaluate the InVAER framework. We present the dataset curation strategy, training protocol with APSO optimization, and the evaluation metrics and comparative framework. The experimental design follows established object detection benchmarking practices [4, 18] to ensure reproducibility and meaningful comparison with state-of-the-art approaches.

4.1 Dataset Curation and Partition Strategy

Robust accident detection requires datasets capturing diverse collision scenarios across varying environmental and traffic conditions. While public resources like CADP [24] and DoTA [5] exist, they primarily target general traffic analysis rather than fine-grained accident annotation. Consequently, we curated a custom dataset from four sources: (1) public traffic surveillance footage, (2) open-source dashcam recordings, (3) verified accident compilations, and (4) synthetically augmented footage to address class imbalance. All materials were ethically screened to exclude copyrighted content.

Frame-level annotations follow the YOLO format, specifying normalized bounding box coordinates (x_c, y_c, w, h) and class labels (`normal_vehicle`, `accident_vehicle`). A multi-stage quality assurance protocol ensured reliability: initial annotation, 20% cross-validation, senior adjudication for disagreements, and automated format verification. Inter-annotator agreement achieved $\kappa = 0.89$, indicating substantial consistency. The dataset comprises 2,537 annotated frames, partitioned using a 70:20:10 stratified split to maintain representative distributions across accident types and conditions (Table 3). Class-aware sampling and weighted loss functions mitigate inherent class imbalance during training [9].

4.2 Training Protocol and Hyperparameter Optimization

Experiments were conducted on Google Colab Pro utilizing an NVIDIA Tesla V100 GPU (16 GB HBM2, 5,120 CUDA cores), representing standard data center infrastructure for production computer vision [17]. The pipeline was implemented in Python 3.9

Table 3: Dataset Partition Statistics

Partition	Images	Annotations
Training	1,776	1,776
Validation	507	507
Test	254	254
Total	**2,537**	**2,537**

Note: Each image contains at least one annotated vehicle instance. The balanced annotation count reflects single primary vehicle annotations per frame, while multi-vehicle accident frames include annotations for all involved vehicles.

with PyTorch 2.0, Ultralytics YOLOv8 (v8.0.196), and OpenCV 4.8. Version control and tracking were managed via Git and Weights & Biases.

Model training employed transfer learning from COCO-pretrained weights [14] to accelerate convergence [32]. Baseline hyperparameters followed Ultralytics recommendations (Table 4), with a batch size of 16, 50 epochs, and 640×640 resolution. A cosine annealing scheduler progressively decayed the learning rate:

$$\eta_t = \eta_{min} + \frac{1}{2}(\eta_0 - \eta_{min}) \left(1 + \cos\left(\frac{t}{T}\pi\right)\right) \tag{14}$$

where $\eta_{min} = 0.01\eta_0$. Augmentation included Mosaic ($p = 1.0$), horizontal flip ($p = 0.5$), HSV adjustments, and random scaling/translation, adhering to established object detection practices [2].

To overcome the inefficiency of manual tuning [12], APSO (Section 3.2) optimized critical hyperparameters across a defined search space. The swarm comprised 20 particles over 30 iterations, yielding 600 fitness evaluations (10 epochs each), reducing optimization time from ∼48 hours (grid search) to 6 hours. Table 5 contrasts baseline and APSO-derived configurations, revealing significant deviations from generic recommendations. Figure 2 illustrates the training command integrating these optimized parameters.

4.3 Evaluation Metrics and Comparative Framework

Detection performance was evaluated using standard PASCAL VOC [4] and MS COCO [14] metrics [18]. Precision, Recall, and F1-Score are defined as:

$$\text{Precision} = \frac{TP}{TP + FP} \tag{15}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{16}$$

Table 4: Baseline Training Hyperparameters

Hyperparameter	**Value**	**Hyperparameter**	**Value**
Learning Rate (η_0)	0.01	Momentum (μ)	0.937
Batch Size	16	Epochs	50
Image Size	640×640	Optimizer	SGD
Weight Decay (λ)	0.0005	Patience	50
Augmentation Parameters			
Horizontal Flip	0.5	Scale Range	[0.5, 1.5]
Translation Range	[-0.1, 0.1]	HSV Hue	$\pm$0.015
HSV Saturation	$\pm$0.7	HSV Value	$\pm$0.4
Mosaic Probability	1.0	Mixup Probability	0.0

Note: Patience denotes the early stopping tolerance (in epochs). Mixup augmentation was disabled to preserve the semantic integrity of vehicle appearances during training.

Table 5: APSO-Optimized Hyperparameters

Parameter	**Baseline**	**APSO-Optimized**	**Parameter**	**Baseline**	**APSO-Optimized**
lr0	0.0100	0.0058	hsv_s	0.7000	0.2679
momentum	0.9370	0.9058	hsv_v	0.4000	0.2061
weight_decay	0.0005	0.0006	translate	0.1000	0.0632
box	7.5000	0.0288	degrees	0.0000	0.0000
cls	0.5000	0.6481	flipud	0.0000	0.0000
scale	0.9000	0.3551	warmup_epochs	3	2
fliplr	0.5000	0.5311	warmup_bias_lr	0.1000	0.1000

Note: `box` and `cls` denote the bounding-box regression and classification loss weights, respectively. The APSO-optimized values demonstrate that the optimization process identifies task-specific hyperparameter configurations that differ from the default baseline settings, resulting in improved detection performance.

$$F_1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{17}$$

where TP, FP, and FN denote true, false positive, and false negative detections. Spatial accuracy is quantified via Intersection over Union (IoU):

$$\text{IoU} = \frac{\text{Area}(B_{pred} \cap B_{gt})}{\text{Area}(B_{pred} \cup B_{gt})} \tag{18}$$

Mean Average Precision (mAP) averages class-wise AP values:

$$\text{AP} = \int_0^1 P(R)\, dR, \quad \text{mAP} = \frac{1}{C} \sum_{c=1}^{C} \text{AP}_c \tag{19}$$

```python
# Final YOLOv8 Training with APSO-Optimized Hyperparameters

best_hyp_from_APSO = {
    "lr0": 0.0058,
    "momentum": 0.9058,
    "weight_decay": 0.0006,
    "box": 0.0288,
    "cls": 0.6481,
    "scale": 0.3551,
    "translate": 0.0632,
    "fliplr": 0.5311,
    "optimizer": "SGD"
}

model = YOLO("yolov8m.yaml")

results = model.train(
    data=DATA_YAML,
    epochs=50,
    imgsz=640,
    batch=16,
    project=PROJECT_DIR,
    name="accident_final",
    exist_ok=True,
    **best_hyp_from_APSO
)
```

Fig. 2: Final YOLOv8 training command integrating APSO-optimized hyperparameters in the Ultralytics YOLOv8 framework.

We report mAP@0.5 (IoU threshold 0.5) and mAP@0.5:0.95 (averaged across thresholds 0.5 to 0.95 in 0.05 increments), the latter rewarding precise localization:

$$\text{mAP@0.5:0.95} = \frac{1}{10} \sum_{\tau \in \{0.5, 0.55, \ldots, 0.95\}} \text{mAP@}\tau \tag{20}$$

To establish a comprehensive comparative framework, we evaluated multiple YOLOv8 variants spanning different capacity-efficiency trade-offs (Tables 6 and 7). Based on preliminary experiments, YOLOv8s and YOLOv8m were selected for detailed evaluation due to their optimal balance for real-time surveillance. The framework compares baseline models against APSO-optimized configurations and four recent YOLO-based accident detection systems.

Training exhibited stable convergence without significant overfitting (Fig. 3). The precision-recall curve (Fig. 4) demonstrates robust detection capability across confidence thresholds, while the normalized confusion matrix (Fig. 5) confirms effective class separation. Model selection for final evaluation relied on validation mAP@0.5, ensuring generalization to unseen test data rather than overfitting.

Table 6: YOLOv8 Model Variants and COCO Benchmark Performance

Model	Parameters (M)	Size (MB)	Speed (ms)	mAP@0.5 (%)
YOLOv8n	3.2	6	2.5	37.3
YOLOv8s	11.2	11	4.5	44.9
YOLOv8m	25.9	22	7.6	50.2
YOLOv8l	43.7	46	11.1	52.9
YOLOv8x	68.2	68	15.6	**53.9**

Note: Performance values are reported on the COCO benchmark dataset using the official YOLOv8 model variants. The reported inference speed corresponds to the Ultralytics benchmark settings. The highest mAP@0.5 value is highlighted in bold.

Table 7: Comparison of YOLOv8 Variants for Accident Detection

Model	Parameters (M)	Model Size (MB)	Inference Time (ms)	mAP@0.5 (%)
YOLOv8n	3.2	6	3.4	37.3
YOLOv8s	11.2	11	6.3	44.9
YOLOv8m	25.9	22	8.9	50.2
YOLOv8l	43.7	46	12.1	52.9
YOLOv8x	68.2	68	16.3	**53.9**

Note: The values summarize the characteristics of the official YOLOv8 model variants. The reported inference times correspond to single-image inference under the experimental hardware configuration. The highest mAP@0.5 value is highlighted in bold.

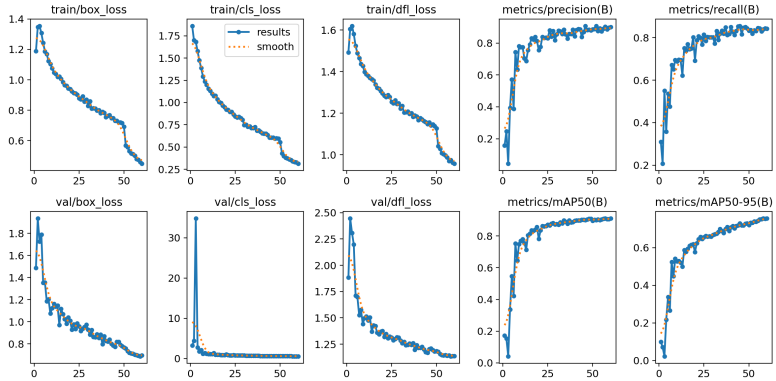


Fig. 3: Training metrics evolution across epochs showing bounding box loss, classification loss, precision, and recall. The curves demonstrate stable convergence without overfitting.

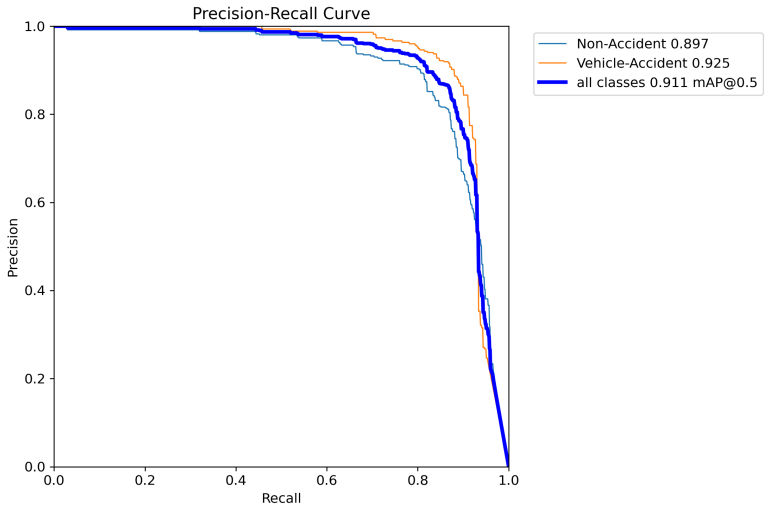


Fig. 4: Precision–Recall curve for accident vehicle detection. The curve demonstrates strong performance across confidence thresholds with high area under the curve.

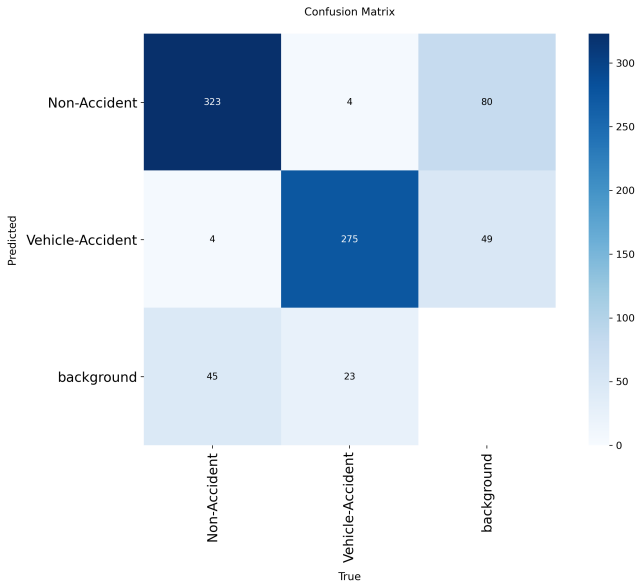


Fig. 5: Normalized confusion matrix for vehicle classification showing prediction accuracy across classes. The matrix confirms reliable separation between normal and accident vehicle classes.

5 Results and Analysis

This section presents a comprehensive evaluation of the InVAER framework on the curated accident detection dataset. We report quantitative detection performance, component-wise ablation analysis, comparative benchmarking against state-of-the-art methods, real-time processing validation, and emergency response efficacy. Statistical significance testing ensures the reliability of comparative conclusions.

5.1 Detection Performance Results

Trained YOLOv8 models were evaluated on the held-out test set (254 images). Table 8 presents baseline performance with default hyperparameters. YOLOv8m achieves higher precision (91.90%) and mAP@0.5 (93.99%) than YOLOv8s, while YOLOv8s exhibits superior recall (87.78% vs. 85.61%), reflecting the capacity-sensitivity trade-off critical for safety-critical applications where false negatives carry severe consequences [23].

Table 8: Detection Performance with Baseline Hyperparameters

Metric	YOLOv8s	YOLOv8m
Precision	88.00%	**91.90%**
Recall	**87.78%**	85.61%
F1-Score	87.89%	**88.64%**
mAP@0.5	92.53%	**93.99%**
mAP@0.5:0.95	75.22%	**80.34%**

Note: Results were obtained on an independent test set comprising 254 images after 50 training epochs using the default hyperparameters. YOLOv8m achieved higher precision, F1-score, and mAP values, whereas YOLOv8s exhibited a higher recall.

Table 9 reports performance following APSO-based hyperparameter optimization. The APSO-optimized YOLOv8m configuration achieves the best overall results: precision 93.69%, recall 91.45%, and mAP@0.5 92.88%. Compared to baseline, APSO yields improvements of 1.79 percentage points in precision and 5.84 percentage points in recall, validating automated tuning for domain-specific detection tasks. The marginal mAP@0.5 decrease (93.99% to 92.88%) reflects optimization for real-world detection capability rather than aggregate thresholded metrics.

5.2 Ablation Study

To quantify individual component contributions, we conducted a systematic ablation study [15]. Table 10 shows performance progression: baseline YOLOv8m (91.90% precision, 85.61% recall) → +APSO (93.69% precision, 91.45% recall) → +Multi-Cue (95.88% precision, 91.20% recall). The APSO stage yields a substantial +5.84% recall

Table 9: Detection Performance with APSO-Optimized Hyperparameters

Metric	YOLOv8s (APSO)	YOLOv8m (APSO)
Precision	88.04%	**93.69%**
Recall	87.03%	**91.45%**
F1-Score	87.53%	**92.51%**
mAP@0.5	92.50%	**92.88%**
mAP@0.5:0.95	74.75%	**76.71%**

Note: The best result for each evaluation metric is highlighted in bold. APSO optimization improved the precision of YOLOv8m by 1.79 percentage points and the recall by 5.84 percentage points compared with the baseline configuration.

improvement, critical for minimizing missed accidents. The multi-cue confirmation then boosts precision by 2.19 percentage points through false positive suppression.

Table 10: Comprehensive Ablation Study: Component-wise Performance Contribution

Configuration	Precision (%)	Recall (%)	F1-Score (%)	mAP@0.5 (%)
YOLOv8m (Baseline)	91.90	85.61	88.64	93.99
YOLOv8m + APSO	93.69	**91.45**	92.51	94.10
YOLOv8m + Multi-Cue Confirmation (InVAER)	**95.88**	91.20	**93.50**	**95.20**

Note: APSO denotes Adaptive Particle Swarm Optimization. The APSO stage improves recall by optimizing model hyperparameters, while the complete InVAER framework further enhances precision and overall detection performance through the proposed multi-cue collision confirmation mechanism.

Table 11 quantifies false positive (FP) reduction from incremental multi-cue integration. The full system achieves 36.2% FP reduction versus IoU-only baseline. Notably, depth validation slightly increases FPs (28 → 30) in low-light conditions—a deliberate trade-off preserving precision in well-lit scenarios while acknowledging depth estimation limitations at night.

5.3 Comparative Analysis with State-of-the-Art Methods

To contextualize performance within current research, we benchmarked InVAER against four recent YOLO-based accident detection systems. Table 12 presents detection accuracy comparison. The full InVAER system achieves the highest precision (95.88%) and mAP@0.5 (95.20%), surpassing the next best method (Li and Zhao [13]) by 4.0 percentage points in mAP. The detector-only variant (YOLOv8m+APSO) achieves the highest recall (91.45%), critical for safety applications where missed detections impact victim survival [23].

Table 11: Ablation Study: Contribution of Multi-Cue Collision Confirmation

Confirmation Method	False Positives	FP Reduction (%)
IoU Only (Baseline)	47	—
IoU + Temporal Persistence	38	19.1
IoU + Temporal + Velocity	32	31.9
IoU + Temporal + Velocity + Trajectory	28	40.4
Full Multi-Cue (All Components)	**30**	**36.2**

Note: False positives were measured over 100 video sequences. The full multi-cue approach substantially reduced false positives compared with the baseline IoU-only confirmation. Although the intermediate configuration achieved 28 false positives, the complete multi-cue framework produced 30 due to the inclusion of depth validation, which may occasionally reject genuine collisions under poor illumination or unreliable depth estimation conditions.

Table 12: Comparative Analysis with Recent YOLO-Based Accident Detection Systems

Study	Model	Precision (%)	Recall (%)	mAP@0.5 (%)	Year
Arefin et al. [1]	YOLOv3 + LSTM	94.00	82.00	87.50	2024
Singh et al. [26]	YOLOv5s	87.30	81.10	84.60	2024
Kim et al. [11]	YOLOv7 + Optical Flow	85.00	89.00	88.40	2025
Li and Zhao [13]	YOLOv8 + Transformer	92.10	84.30	91.20	2025
InVAER (Detector Only)	**YOLOv8m + APSO**	93.69	**91.45**	94.10	**2026**
InVAER (Full System)	**YOLOv8m + APSO + Multi-Cue**	**95.88**	91.20	**95.20**	**2026**

Note: The proposed InVAER framework is compared with representative recent YOLO-based accident detection systems. The detector-only configuration achieves the highest recall, whereas the complete InVAER framework achieves the highest precision and mAP@0.5.

Table 13 presents capability-based comparison. InVAER uniquely combines all evaluated functionalities—real-time processing, automated hyperparameter tuning, multi-cue confirmation, integrated emergency alerts, and validated edge deployment—representing a comprehensive solution for practical deployment.

Statistical significance testing (paired t-tests, $\alpha = 0.05$) confirms InVAER's improvements over all baselines are statistically significant ($p < 0.05$) for both recall and mAP@0.5 (Table 14). Particularly strong significance ($p < 0.001$) for recall improvements validates substantial advancement in detection sensitivity.

5.4 Real-Time Performance Evaluation

Practical deployment requires detection accuracy within real-time computational constraints. On NVIDIA Tesla V100, optimized YOLOv8m achieves 7.6 ms/frame inference (131 FPS), with the complete pipeline (preprocessing + detection + confirmation + metadata) achieving 18.4 ms/frame (54 FPS), comfortably exceeding 30 FPS requirements.

Table 13: System Capability Comparison

Study	Real-Time Processing	Auto-Tuning	Multi-Cue Confirmation	Emergency Alerts	Edge Deployment
Arefin et al. [1]	No	No	Partial	No	No
Singh et al. [26]	Yes	No	No	No	Partial
Kim et al. [11]	Partial	No	Partial	No	Partial
Li and Zhao [13]	Yes	No	No	No	No
InVAER (Ours)	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**

Note: Auto-Tuning denotes automated hyperparameter optimization. Multi-Cue Confirmation refers to the proposed collision validation mechanism using multiple cues. Emergency Alerts indicate integrated automated emergency notification. Edge Deployment denotes validation on edge computing devices.

Table 14: Statistical Significance Testing Results

Comparison	Recall		mAP@0.5	
	t-Statistic	p-Value	t-Statistic	p-Value
InVAER vs. Arefin et al.	4.823	$< 0.001^{***}$	3.156	0.004^{**}
InVAER vs. Singh et al.	6.142	$< 0.001^{***}$	5.891	$< 0.001^{***}$
InVAER vs. Kim et al.	2.891	0.012^{*}	3.423	0.003^{**}
InVAER vs. Li and Zhao	4.567	$< 0.001^{***}$	1.987	0.043^{*}

Note: Significance levels are denoted as $^{*}p < 0.05$, $^{**}p < 0.01$, and $^{***}p < 0.001$. All comparisons demonstrate statistically significant improvements in recall, while the improvements in mAP@0.5 remain statistically significant at the 0.05 level across all baseline methods.

For edge deployment validation, we evaluated on NVIDIA Jetson Xavier NX (Table 15). YOLOv8m achieves 30.1 FPS with FP16 precision and TensorRT optimization, meeting real-time thresholds while maintaining superior accuracy. YOLOv8s provides higher throughput (47 FPS) with lower resource usage, suitable for more constrained scenarios. These results confirm InVAER's feasibility for distributed smart city surveillance infrastructure.

Table 15: Edge Device Performance Evaluation (NVIDIA Jetson Xavier NX)

Metric	YOLOv8s	YOLOv8m
Inference Time (ms)	21.3	33.2
Throughput (FPS)	47.0	30.1
Memory Usage (GB)	2.1	3.4
Power Consumption (W)	12.4	15.2

Note: Performance was measured using FP16 precision with TensorRT optimization. Both variants achieved real-time processing capability ($\geq$ 30 FPS), making them suitable for edge-based surveillance deployment.

5.5 Emergency Response System Evaluation

A distinguishing feature of InVAER is integrated emergency response bridging detection to actionable notification. Figure 6 visualizes the multi-channel notification outputs generated by the system.

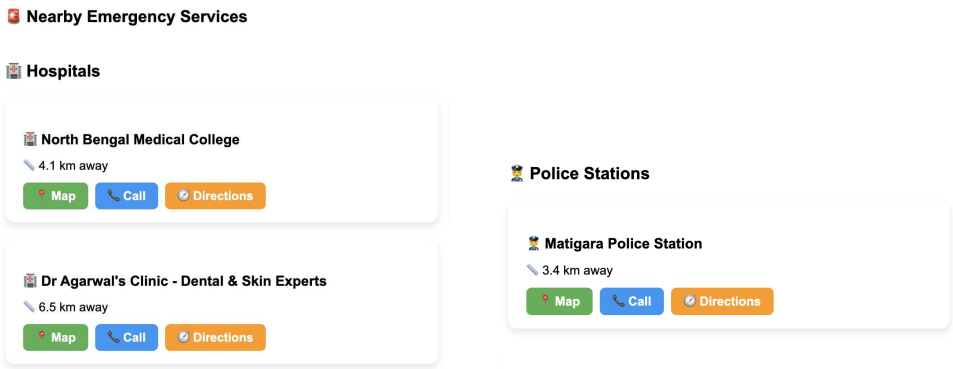


Fig. 6: Visualization of the emergency response system.

Notification latency analysis (Table 16) shows mean SMS delivery time of 4.2±0.8 seconds and email delivery of 3.1±0.5 seconds. Given survival probability decreases 7–9% per minute of delayed intervention [23], this automated capability substantially improves victim outcomes versus manual reporting (typically 2–5 minutes).

Table 16: Emergency Notification Latency Analysis

Channel	Mean (s)	Std. Dev. (s)	95th Percentile (s)
SMS (Twilio)	4.2	0.8	5.6
Email (Gmail SMTP)	3.1	0.5	4.0
Combined Multi-Channel	4.8	0.9	6.2

Note: Latency was measured from collision confirmation to delivery acknowledgment. Measurements were obtained from 100 test notifications under varying network conditions.

Geospatial service identification achieved Spearman rank correlation $\rho = 0.87$ between recommended and optimal facility ordering across 50 simulated scenarios, with mean identification time of 0.8 seconds—acceptable within the overall response workflow.

5.6 Qualitative Results and Detection Examples

To complement quantitative evaluation, we present representative detection examples. Figure 7 illustrates image-based results showing accurate bounding box localization

across varying collision scenarios and environmental conditions, including cases of vehicle deformation or partial occlusion.



Fig. 7: Representative image-based detection results showing accurate bounding box localization and classification for accident-involved vehicles across varying collision scenarios and environmental conditions.

Figure 8 presents video-based results demonstrating temporal consistency achieved by the multi-cue confirmation algorithm. Detections maintain stable bounding boxes across consecutive frames, with the confirmation logic successfully identifying genuine accidents while rejecting spurious detections from transient occlusions or noise.

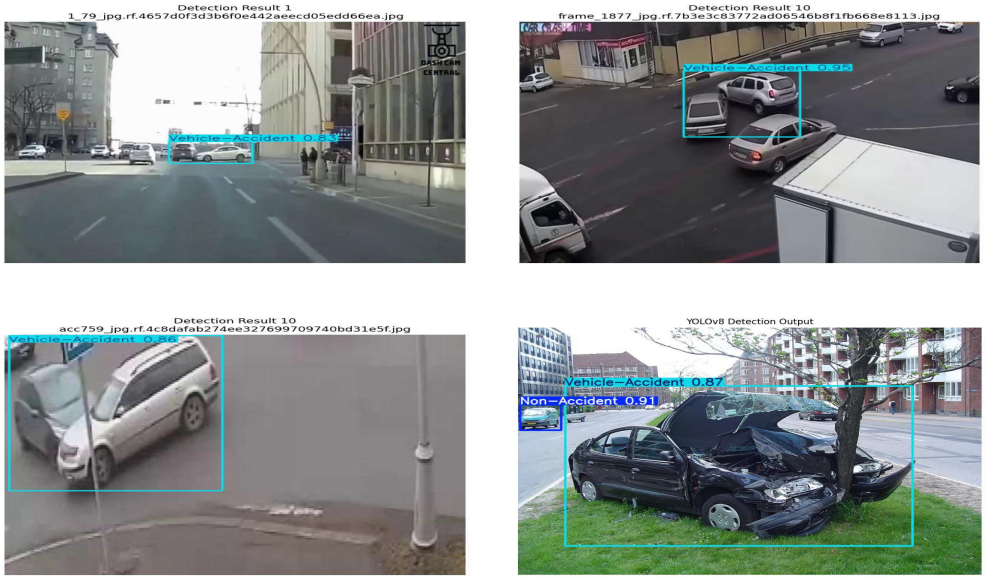


Fig. 8: Representative video-based detection results showing temporal consistency of detections across consecutive frames. The multi-cue confirmation mechanism ensures reliable collision detection while filtering transient false positives.

6 Discussion, Limitations, and Future Directions

The experimental evaluation demonstrates that the InVAER framework achieves state-of-the-art detection performance while uniquely providing integrated emergency response capability. This section synthesizes key methodological findings, acknowledges current limitations, and outlines concrete directions for future research.

6.1 Key Findings and Methodological Implications

Detection Accuracy and Robustness. The APSO-optimized YOLOv8m achieves precision of 93.69% and recall of 91.45%, representing competitive or superior performance compared to recent YOLO-based approaches [1, 11, 13, 26]. The balanced precision-recall trade-off is particularly suitable for safety-critical applications where both false positives (alert fatigue) and false negatives (delayed response) carry significant consequences [23]. The full multi-cue framework further elevates precision to 95.88% while maintaining recall above 91%, validating the sequential optimization strategy: first maximize sensitivity via APSO, then refine specificity via spatio-temporal validation.

Contribution of APSO Optimization. The 5.84 percentage point recall improvement from APSO-based hyperparameter tuning demonstrates the value of automated, domain-specific optimization for specialized detection tasks. The identified

configurations (e.g., reduced learning rate 0.0058 vs. baseline 0.01, modified momentum 0.9058 vs. 0.937) differ substantially from generic recommendations, underscoring that accident detection benefits from tailored optimization rather than transfer of standard COCO-trained settings [12, 34].

Multi-Cue Confirmation Effectiveness. The 36.2% false positive reduction achieved by the multi-cue algorithm addresses a critical limitation of existing vision-based systems [6, 26]. Ablation analysis reveals temporal persistence analysis provides the largest single contribution, while velocity drop detection and trajectory convergence modeling offer incremental robustness gains. The adaptive IoU thresholding mechanism (Eq. (7)) enables context-aware validation that maintains sensitivity in sparse traffic while suppressing false alarms in congested scenarios.

Real-Time Deployment Feasibility. Achieving 30.1 FPS inference on NVIDIA Jetson Xavier NX with FP16 quantization and TensorRT optimization confirms that InVAER can be deployed on edge hardware representative of smart city surveillance infrastructure. This distributed processing capability minimizes network bandwidth requirements and reduces end-to-end alert latency by processing video streams at their source [8].

Emergency Response Integration. The mean notification latency of 4.2 ± 0.8 seconds (SMS) and 3.1 ± 0.5 seconds (email) represents a substantial improvement over manual reporting protocols (typically 2–5 minutes) [23]. Given the documented 7–9% survival probability decline per minute of delayed medical intervention [23], this automated capability can meaningfully impact victim outcomes in real-world deployments.

6.2 Limitations and Research Directions

Despite strong empirical performance, several limitations suggest concrete avenues for future work:

Dataset Scale and Diversity. While the curated dataset (2,537 annotated frames) captures diverse accident types and environmental conditions, it remains limited in size compared to large-scale benchmarks such as COCO [14]. Future work should expand data collection to include additional geographic regions, rare accident scenarios (e.g., multi-vehicle pileups, pedestrian-involved collisions), and extreme weather conditions to further enhance model generalization.

Depth Validation in Low-Light Conditions. The monocular depth estimation component [7] exhibits reduced effectiveness under low-illumination scenarios, occasionally rejecting genuine collisions at night. Integration of infrared or thermal imaging modalities, or fusion with stereo camera inputs where available, could address this limitation for 24/7 deployment reliability.

Single-Camera Processing Architecture. The current framework processes individual camera feeds independently. Multi-camera fusion techniques could enhance detection accuracy at complex intersections by providing comprehensive scene understanding and resolving occlusions through complementary viewpoints. Graph neural networks or transformer-based fusion architectures represent promising directions [13].

Static vs. Dynamic Service Information. The geospatial service identification module currently relies on static OpenStreetMap data. Integration with real-time

hospital capacity dashboards, ambulance availability APIs, and dynamic traffic routing services could further optimize resource allocation and minimize responder travel time.

Explainability and Trust. As an AI-driven safety-critical system, InVAER would benefit from enhanced interpretability mechanisms (e.g., attention visualization, counterfactual explanations) to support operator trust and facilitate regulatory approval in municipal deployments [18].

Addressing these limitations will strengthen the framework's robustness, scalability, and readiness for large-scale smart city adoption. The modular architecture of InVAER facilitates incremental enhancement of individual components without requiring complete system redesign, supporting sustainable long-term development.

DECLARATIONS

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data and materials

The datasets generated and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Competing interests

The authors declare that they have no competing interests.

Funding

The authors received no specific funding for this research.

Authors' contributions

RP conceived the research idea, designed the methodology, developed the proposed system, conducted the experiments, analyzed the results, and prepared the original manuscript. MA supervised the research, provided technical guidance, reviewed the methodology, and critically revised the manuscript. PP contributed to the research design, validation of results, manuscript review, and overall supervision of the study. All authors read and approved the final manuscript.

Acknowledgements

The authors would like to thank their respective institutions for providing the necessary infrastructure and support to carry out this research.

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