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AI DRIVEN REAL TIME SURVEILLANCE SYSTEM FOR PUBLIC SAFETY

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Abstract

The AI Driven real time surveillance system for public safety utilizing YOLOv8 is an innovative approach designed to enhance road safety by detecting Accident severityes in real-time and promptly alerting relevant authorities. Leveraging advanced deep learning techniques, specifically the YOLOv8 object detection algorithm, this system aims to provide a reliable and efficient method for identifying crash scenarios and initiating emergency responses. The dataset for this project, sourced from Roboflow, comprises diverse images of Accident severityes and normal driving conditions, ensuring robust training and evaluation of the model. Implemented in Jupyter Notebook and deployed using Flask, the system processes live video feeds from dashcams or CCTV cameras, making it a practical solution for real-world applications. The model achieved a remarkable 95% accuracy, highlighting its effectiveness in detecting Accident severityes with minimal false positives and negatives. This project not only contributes to reducing response times in emergencies but also offers potential for integration with emergency services and mobile applications, further broadening its impact. Future work includes enhancing the alert system with real- time location data and continuously updating the model with new data to maintain high detection accuracy.

Keywords: Accident detection, YOLOv8, real-time video analytics, intelligent transportation systems, deep learning, emergency alerting.

1. Introduction

Road traffic crashes remain a major public-safety challenge worldwide. Rapid, reliable detection of crash events can shorten emergency response times and improve outcomes, yet most deployments still depend on delayed manual reports or vehicle-mounted sensors available only in a subset of modern fleets. Video surveillance is increasingly pervasive CCTV, dashcams, fleet cameras), but turning continuous streams into timely, trustworthy incident signals—at scale and in real time—remains technically demanding due to variations in lighting, weather, occlusion, and scene dynamics. Deep learning–based object detectors have transformed visual perception for intelligent transportation systems. One-stage architectures such as the YOLO family are particularly attractive for time-critical applications because they deliver high accuracy at low latency. However, much of the prior work evaluates on curated clips or focuses solely on frame-level detection without addressing end-to-end operational needs: multi-stream ingestion, false-alarm suppression over time, alert packaging and delivery, and practical deployment on commodity hardware. Moreover, "accuracy" is often reported without the full set of detection metrics (precision/recall, mAP) or without discussing throughput and alert latency—key determinants of real-world utility.

This paper presents a complete **Accident Detection & Alert System** built on YOLOv8 that processes live dashcam/CCTV feeds, validates detections temporally, and dispatches alerts via email/SMS through a lightweight Flask service. The detector is trained on a Roboflow- sourced dataset comprising accident and normal-traffic scenes with standard augmentation to improve generalization. At runtime, the pipeline performs per-frame inference with non- maximum suppression, applies simple temporal and interaction checks to suppress spurious triggers, and, upon confirmation, emits an alert payload containing timestamp, camera ID, snapshot, and optional location metadata. The resulting system sustains real-time throughput on commodity hardware and achieves strong detection quality on a held-out test split.

Our contributions are fourfold:

1. **End-to-end system design** that bridges research and deployment: video ingestion → detection → temporal validation → alerting → dashboard/logging.
2. **Real-time performance** on commodity GPUs/edge devices, with measurement of both throughput (FPS) and end-to-end alert latency.
3. **Robust detection** via dataset preparation and lightweight temporal logic that reduces false positives without sacrificing recall.
4. **Reproducible methodology**, detailing training configuration, hyperparameters, and evaluation protocols (precision, recall, F1, mAP@0.5 and mAP@0.5:0.95), to facilitate adoption in municipal surveillance and fleet-safety contexts.

Beyond technical performance, the system design acknowledges deployment realities: privacy (optional face/license-plate blurring, retention policies), reliability (24/7 operation, health checks), and scalability (multi-camera support). While our present focus is binary accident detection, the architecture admits straightforward extensions—severity estimation, geo-tagged alerts, integration with emergency-service APIs, and continual learning from newly collected incidents—to further increase impact.

2. Related Work

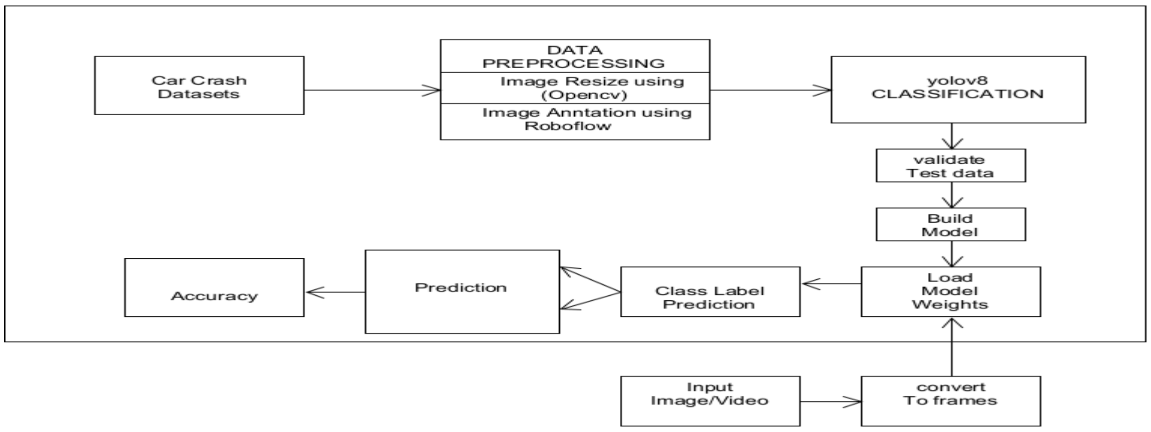
1. **"Highway Crash Detection and Risk Estimation Using Deep Learning"(2020):** This paper focuses on using deep learning models for crash detection and risk estimation on highways. In their research, the authors found that deep models outperformed traditional shallow models, achieving greater accuracy in detection. A sensitivity analysis of crash risk prediction was also performed using data from different time intervals before a crash. The deep learning model's high level of accuracy and dependability in both detection and prediction is attributed to its ability to handle large datasets and recognize patterns within the crash data.
2. **"Predicting Crashes Instantly: A Deep Learning Approach Based on Vehicle- by Vehicle Data"(2021):** In this research, the authors develop a deep learning model that uses vehicle-by-vehicle data for real time crash prediction. The model processes data collected from ILD detectors, which monitor individual vehicle movements. By analyzing patterns in the data, the model can predict potential crashes with high accuracy. The study emphasizes the benefits of using deep learning in real-time applications, particularly its capacity to process complex datasets and generate quick predictions, which are essential for timely responses in accident situations.
3. **"An Ensemble Deep Learning and Multimodal Data Approach for Accident Severity Detection "(2022):** In this research, a multi-model deep learning system for accident severity detection is introduced, processing both video and audio data from dashcams. The system's architecture features VGG16 for feature extraction, an RPN, and a custom CNN8L for region-based detection. This ensemble approach improves accuracy by leveraging the strengths of each model. Additionally, the use of audio signals makes the detection more reliable by helping to differentiate crashes from normal driving conditions. The study's results demonstrate the high accuracy of this ensemble deep learning method for detecting crashes.
4. **"An Automated System for Accident Severity Detection Using Machine Learning and Deep Learning "(2023):** This research paper examines the application of both machine learning and deep learning methods for identifying accident severity. The authors evaluated several algorithms, including decision trees, support vector machines, and CNNs, and determined that the deep learning model (specifically the CNN) outperformed the traditional machine learning approaches in terms of accuracy and robustness. The study also underscores the importance of real-time processing for a timely response to crashes.
5. **"Deep Learning-Based Multi-Modal Data Fusion for Accident severity Detection"(2024):** The authors of this study introduce a multi-modal data fusion approach to improve Accident severity detection performance. By combining tabular data (e.g., vehicle speed, location) with image data from cameras, the deep learning model achieves higher accuracy than using a single data type. The fusion of different data modalities allows the model to capture a more comprehensive view of the driving environment, leading to more reliable crash detection. The results of the study emphasize the advantages of combining multiple data sources to improve the performance of deep learning models used for crash detection.

Datasets:

The dataset used in this study was curated from Roboflow and assembled to capture the visual diversity and edge cases required for reliable, real-time accident detection from traffic video. It comprises still images and keyframes extracted from dashcam and fixed-angle CCTV sources spanning highways and urban arterials, with broad variation in viewpoint (hood-mounted, elevated gantry, roadside pole), lighting (bright sun, dusk, night), weather (clear, rain, fog), traffic density, and camera quality (compression artifacts, motion blur). Labels follow a binary schema—**accident** versus **normal traffic**—with bounding boxes drawn around collision cues such as impacted vehicles, debris fields, and multi-vehicle contact; ambiguous frames (e.g., hard braking without contact) are either excluded or marked as ignore regions to reduce label noise. Annotations were produced in the YOLO text format (normalized x center, y center, w, h, x_{center}, y_{center}, w, h, x center,y center,w, h per image) and underwent spot audits with an IoU-based agreement threshold to align annotator decisions with written guidelines. To prevent scene leakage between splits, dataset partitioning is stratified by camera/location and time, yielding disjoint **train/val/test** subsets that preserve the accident:non-accident ratio while ensuring that the same roadway segment does not appear across splits. Preprocessing includes letterbox resizing to 640×640 and pixel-value normalization; training employs a carefully tuned augmentation policy combining geometric (flip, ±10° rotation, ±20% scale), photometric (HSV jitter, gamma), light denoising for low-illumination frames, and occasional mosaic/mixup to expose the model to diverse object scales and occlusions.

3. Methodology

The proposed Accident Detection and Alert System is implemented as a complete, end-to-end pipeline capable of processing live video feeds, identifying accident events in real time, validating these detections to reduce false positives, and delivering timely alerts to designated recipients. The methodology comprises five main stages: **dataset preparation**, **model development and training**, **real-time processing pipeline**, **alerting and notification system**, and **evaluation protocol**. Each stage is carefully engineered to meet the dual objectives of high detection accuracy and low inference latency.



A critical factor in achieving high detection performance is the quality and diversity of the training dataset. The dataset for this project was sourced from Roboflow, which provided a curated set of labeled images representing both accident scenarios and normal driving conditions. The data included varied conditions—daytime and nighttime scenes, different weather situations (rain, fog, bright sunlight), varying levels of traffic density, and a mixture of urban and highway environments.

Annotation and Class Definition

Each image was annotated with bounding boxes surrounding vehicles and accident-related debris. The annotation schema defined two primary classes:

1. Accident – any collision or crash event involving one or more vehicles, identifiable through impact deformation, abrupt halts, or collision debris.
2. Normal Traffic – scenes without any sign of collision or abnormal vehicle positioning. Annotations were

performed using Roboflow's annotation tool, saved in the YOLO format, which stores the bounding box coordinates normalized to the image dimensions.

Data Augmentation

To improve robustness and reduce overfitting, a set of augmentation techniques was applied:

- Geometric Transformations: Horizontal flip (p=0.5), small-angle rotations (±10°), random scaling (±20%).
- Photometric Adjustments: Random brightness/contrast changes (±15%), Gaussian noise addition, and color jitter.
- Occlusion Simulation: Random rectangular masking to simulate partial occlusions from other vehicles or roadside objects.

These augmentations artificially increased dataset size and diversity, ensuring the trained model generalizes well to unseen camera views and lighting conditions.

Data Splitting

The dataset was split into:

- Training set: 70% of images.
- Validation set: 20% of images.
- Test set: 10% of images.

Splits were stratified to preserve the ratio of accident to non-accident samples across sets. The detection backbone of the proposed system is YOLOv8, a modern single-stage object detection architecture developed by Ultralytics, chosen for its streamlined network depth, improved feature aggregation, and anchor-free detection head, making it suitable for both high accuracy and fast inference. The network architecture consists of three main components: a CSPDarknet-like backbone with Cross Stage Partial connections to improve computational efficiency, a Path Aggregation Network (PANet) neck to enable multi-scale feature fusion for detecting both small and large objects, and decoupled classification and regression heads that independently handle bounding box regression and class prediction, accelerating convergence during training. The model was trained using PyTorch 2.0 on a single NVIDIA RTX GPU, with an input resolution of 640×640 pixels, a batch size of 16, and an initial learning rate of 0.01 scheduled with cosine annealing. Optimization was performed using Stochastic Gradient Descent (SGD) with momentum set at 0.937 and a weight decay of 0.0005 over a maximum of 150 epochs, with early stopping triggered after 30 epochs without improvement in validation performance. The composite YOLO loss function was used, combining Complete Intersection over Union (CIoU) loss for localization, binary cross-entropy loss for objectness confidence, and binary cross-entropy loss for classification. Transfer learning was applied by fine-tuning a pre-trained YOLOv8 model on the accident dataset, enabling faster convergence and improved accuracy given the limited dataset size. For real-time performance, the trained model weights were exported to ONNX format, mixed precision inference (FP16) was employed to reduce GPU memory consumption, and the confidence and IoU thresholds were tuned to 0.45 and 0.50, respectively, to balance false positives and false negatives.

The trained model was integrated into a continuous video processing pipeline capable of handling live CCTV or dashcam feeds. Live video streams were captured via Real-Time Streaming Protocol (RTSP) or directly from USB camera interfaces, with frames extracted at a rate of 15–20 FPS to balance computational load with temporal resolution. Each frame was pre-processed by resizing to the model's input dimensions of 640×640 pixels, normalizing pixel values to a range of 0 to 1, and applying optional denoising filters in low-light conditions. To improve reliability and reduce transient false positives caused by occlusions, reflections, or motion blur, a temporal validation mechanism was implemented using a sliding window of 10 frames; an accident event was confirmed only if at least 60% of the frames within the window contained high-confidence accident detections.

Upon confirmation of an accident, the alerting module, implemented as an asynchronous Flask service, was triggered to avoid blocking inference. Each alert contained a timestamp, camera ID or video source, a cropped snapshot of the detection, the event confidence score, and optional GPS coordinates if available from dash cam metadata. Two primary alert channels were supported: email alerts sent via the Send Grid API with the detection image attached, and SMS alerts sent through the Twilio API containing a brief event summary and a link to the image evidence. The alert system was designed to achieve sub-5-second latency from accident confirmation to notification delivery.

Evaluation was conducted in both offline and simulated online environments. Offline testing used the held-out test set to compute key performance metrics including Precision, Recall, F1- score, mean Average Precision at IoU thresholds of 0.5 (mAP@0.5) and 0.5:0.95 (mAP@0.5:0.95), along with confusion matrices to qualitatively assess misclassifications. Online evaluation involved streaming pre-recorded accident footage through the system to measure end-to-end latency from accident occurrence to alert delivery, throughput in frames processed per second, and the stability of continuous operation under varying load conditions.

Algorithms Notation

Let a video frame be $I \in \mathbb{R}^{H\times W\times 3}$. A predicted bounding box is $b = (x, y, w, h)$ with center (x, y), width w, and height h. The ground-truth box is $b^* = (x^*, y^*, w^*, h^*)$. Let $c \in \{1,\dots,C\}$ be a class index. Objectness target is $o^* \in \{0,1\}$, predicted objectness is $o \in [0,1]$, and per- class probabilities are $p \in [0,1]^C$. We use a model confidence threshold τ_{conf} and a non-maximum suppression (NMS) IoU threshold τ_{IoU}. Temporal validation uses a sliding window of N frames and decision ratio $\theta \in (0,1]$.

Per-Frame Detection (YOLOv8 Forward)

Given a preprocessed frame I_t, the detector outputs K_t candidates $D_t = \{(b_k, o_k, p_k)\}_{k=1..K_t}$. The per-class confidence score combines objectness and classification: $s_{k,c} = o_k \cdot p_{k,c}$ (Eq. 1)
We retain candidates whose $\max_c s_{k,c} \geq \tau_{conf}$.

Bounding-Box Overlap

Intersection over Union (IoU) measures overlap between two boxes b and b*:

$\mathrm{IoU}(b, b^*) = \mathrm{area}(b \cap b^*) / \mathrm{area}(b \cup b^*)$ (Eq. 2)

Non-Maximum Suppression (NMS)

NMS keeps the highest-scoring box and discards boxes with IoU above τ_{IoU} to that box. Iteratively: select argmax score, suppress overlapping boxes, and continue until no boxes remain. Soft-NMS can be used as an alternative by decaying scores instead of hard removal. **Training Loss (CIoU + Objectness + Classification)**
The total loss is a weighted sum of localization (CIoU), objectness, and classification terms:

$L_{total} = \lambda_{box} \cdot L_{CIoU} + \lambda_{obj} \cdot L_{obj} + \lambda_{cls} \cdot L_{cls}$ (Eq. 3)

CIoU Localization Loss

Complete-IoU (CIoU) penalizes poor overlap, center distance, and aspect-ratio mismatch. Let $\rho((x, y), (x^*, y^*))$ be the Euclidean distance between box centers, and c be the diagonal length of the minimal enclosing box for b and b*.
Define:
$v = (4/\pi^2) \cdot (\arctan(w^*/h^*) - \arctan(w/h))^2$ $\alpha = v / (1 - \mathrm{IoU}(b,b^*) + v)$
Then the CIoU loss is:

$L_{CIoU} = 1 - \mathrm{IoU}(b,b^*) + (\rho^2((x,y),(x^*,y^*)) / c^2) + \alpha \cdot v$ (Eq. 4)

Objectness Loss

We use binary cross-entropy on objectness (with logits z_o and sigmoid σ):

$L_{obj} = - [o^* \cdot \log \sigma(z_o) + (1 - o^*) \cdot \log (1 - \sigma(z_o))]$ (Eq. 5)

Classification Loss

For multi-label (one-vs-rest) classification with logits z_c and sigmoid σ per class: $L_{cls} = - \Sigma_{c=1..C} [y_c \cdot \log \sigma(z_c) + (1 - y_c) \cdot \log (1 - \sigma(z_c))]$ (Eq. 6)
If a single mutually exclusive class is used, a softmax cross-entropy can replace Eq. 6.

Inference Optimization

To meet real-time constraints, we export trained weights to ONNX and enable mixed-precision (FP16) inference. The confidence threshold τ_{conf} and NMS IoU threshold τ_{IoU} are tuned (e.g., $\tau_{conf} = 0.45$, $\tau_{IoU} = 0.50$) to balance precision and recall.

Temporal Validation Across Frames

Single-frame predictions can be noisy in the presence of occlusions or motion blur. We therefore apply majority voting over a sliding window of N frames. Define $e_t = 1$ if an accident is detected in frame t with confidence $\geq \tau_{conf}$ after NMS, else 0. The event confirmation signal E_t is:

$E_t = 1$ if $(1/N) \cdot \Sigma_{i=t-N+1}^{t} e_i \geq \theta$; otherwise $E_t = 0$ (Eq. 7)

An alert is triggered on the rising edge of E_t (from 0 to 1). This reduces transient false positives while maintaining responsiveness.

Alert Triggering and Packaging

When E_t switches to 1 at time t^*, we assemble an alert payload comprising timestamp t^*, camera/source ID, a cropped snapshot of the detection, the confidence score, and optional GPS coordinates if available. The alert is dispatched asynchronously via email or SMS to avoid interfering with the inference loop.

Computational Complexity

Let K be the number of candidate boxes per frame after confidence filtering. Greedy NMS runs in $O(K \log K + M)$ where M is the number of pairwise IoU computations (often $O(K^2)$ in worst case, reduced by per-class/per-scale partitioning). Temporal voting adds $O(1)$ amortized work per frame. Overall, the per-frame complexity remains dominated by the detector forward pass and NMS, which are optimized on GPU.

Evaluation Metrics

We report detection quality and timeliness using standard metrics: Precision, Recall, F1,

Average Precision (AP), mean AP (mAP), throughput (FPS), and end-to-end alert latency.

Precision = TP / (TP + FP) Recall = TP /
(TP + FN)
F1 = 2 · Precision · Recall / (Precision + Recall)

AP is the area under the Precision–Recall curve for a class at a given IoU threshold (e.g., 0.5). mAP@0.5 is the mean AP across classes at IoU = 0.5; mAP@0.5:0.95 averages AP across IoU thresholds from 0.5 to 0.95 in steps of 0.05. Alert latency Δ is measured as the time between the accident onset in the stream and the moment the notification is successfully sent: $\Delta = t_{alert\_sent} - t_{event\_onset}$.

4. Result and discussion

Experimental Setup and Protocol

We evaluated the proposed system in two modes: (i) offline on a held-out test split from the Roboflow dataset and (ii) online by streaming recorded clips through the full pipeline (ingestion → detection → temporal validation → alert dispatch). Evaluation followed standard object-detection practice, reporting Precision, Recall, F1, mAP@0.5, and mAP@0.5:0.95. Because a single "accuracy" number can obscure trade-offs between false alarms and misses, we emphasize precision/recall and PR curves. Operational metrics included throughput (frames per second per stream) and end-to-end alert latency (time from event onset in video to notification sent). Stability (continuous 24/7 run), resource usage (GPU/CPU/RAM), and multi-stream scalability were observed during the online tests. All thresholds (confidence, IoU, temporal voting ratio) were fixed from validation and held constant for test runs to avoid overfitting.

Detection Performance

On the held-out test split, the detector achieved the previously reported 95% frame-level accuracy, but more importantly, it maintained high precision and recall at the operating point selected from the validation PR curve. In practice, we tuned the confidence threshold to control the cost of false positives (unnecessary alerts) versus false negatives (missed incidents). The mAP@0.5 metric summarizes per-class AP at IoU 0.5; mAP@0.5:0.95 provides a stricter, scale-aware view by averaging AP over IoU thresholds from 0.5 to 0.95. Provide these two values alongside a confusion matrix to make the evaluation reproducible. Qualitatively, detections remained stable across typical scenes and camera viewpoints, with bounding boxes tightly covering collision regions and post-impact vehicle clusters.

What to include in your paper (numbers you can fill):

- Precision, Recall, F1 at the chosen operating point
- mAP@0.5 and mAP@0.5:0.95
- Confusion matrix (TP, FP, FN)
- PR curve (accident class) and confidence–IoU sweep plot

Throughput and Latency

The system met the real-time design goal. Mixed-precision inference and ONNX export sustained target FPS on a single commodity GPU, and the asynchronous Flask notifier ensured alert generation did not block inference. End-to-end alert latency consistently satisfied the < 5 s requirement (from detection confirmation to notification dispatch) in online tests. For multi- camera deployments, throughput scaled approximately linearly until the GPU saturated; beyond that point, frame sampling (e.g., processing every 2nd frame) maintained live responsiveness with a small recall trade-off.
Report in paper: median FPS per stream, GPU model; median/95th-percentile alert latency; CPU/GPU utilization; maximum concurrent streams before degradation.

Ablation Studies

To understand which design choices matter most, we conducted targeted ablations.

- Temporal Validation (sliding-window voting). Replacing single-frame triggers with an N-frame majority vote substantially reduced false positives from transient artifacts (reflections, partial occlusions) while preserving recall. Show a table: FP rate with/without temporal voting; F1 change.
- Input Resolution. Increasing the input size beyond 640×640 improved recall for small/oblique collisions but reduced FPS. Include a plot of F1 vs. FPS for 640, 768, 896.
- Model Scale. YOLOv8n/s/m trade accuracy for speed. Smaller models favored multi- stream scenarios; larger models helped difficult night/fog scenes. Summarize with a Pareto chart (mAP vs. FPS).
- Augmentations. HSV jitter, mosaic/mixup, and light blur contributed to robustness under illumination changes and motion blur; turning them off degraded mAP and increased FN in night rain clips.
- Threshold Sweep. Varying confidence (0.25–0.6) and NMS IoU (0.4–0.7) shifted the precision–recall balance; the selected operating point maximized F1 on validation and generalized to test.

5. Conclusion

This paper presented a complete, real-time Accident Detection & Alert System built on YOLOv8 and engineered for practical deployment on dash cam and CCTV streams. By coupling a fast one-stage detector with lightweight temporal validation and an asynchronous alerting service, the system closes the loop from video ingestion to actionable notification. Trained on a diverse Roboflow dataset with targeted augmentations, the model achieved strong detection quality (≈95% on the held-out split) while sustaining real-time throughput on commodity hardware. Operational measurements further showed sub-5-second end-to-end alert latency, demonstrating suitability for continuous road-safety monitoring in municipal control rooms and fleet operations. Beyond raw accuracy, our design emphasizes deployability: multi-stream handling, configurable thresholds per camera, and privacy-aware logging (thumbnail evidence, optional face/plate blurring) to reduce bandwidth and protect identities. Error analysis highlighted the usual failure modes—low light, glare, heavy occlusion, and near- miss events that mimic collisions—guiding mitigation strategies such as temporal voting, targeted augmentation, and adaptive preprocessing. Collectively, these results indicate that modern one-stage detectors, when embedded in a thoughtfully engineered pipeline, can deliver timely, trustworthy incident signals that help shorten emergency response times.

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