AI-based Monitoring of Urban Public Transport Safety Using Computer Vision

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Abstract
Urban public transport systems are essential for city mobility but face persistent safety challenges—vandalism, overcrowding, slip-and-fall incidents, theft, and near-miss collisions at stops. This paper presents a comprehensive framework for real-time monitoring of urban public transport safety using computer vision and deep learning. The proposed system integrates multi-camera feeds, edge-compute modules, and a lightweight deep neural pipeline for event detection (falls, fights, crowding, unattended objects), anomaly scoring, and operator alerting. We evaluate the approach on a mixed dataset collected from bus interiors, tram platforms, and bus stops, achieving an average precision of 0.88 for event detection and a mean time-to-alert under 2.2 seconds on edge hardware. We also discuss privacy-preserving strategies, deployment considerations, and a roadmap for integrating the approach with existing transport management centers.

Keywords: computer vision, public transport safety, anomaly detection, real-time monitoring, edge computing, privacy-preserving AI

1. Introduction
Rapid urbanization has increased demand for safe, reliable public transport. Cities worldwide struggle to maintain passenger safety inside vehicles and at stops, especially during peak hours. Traditional monitoring relies on human operators viewing CCTV feeds, which is error-prone, labor-intensive, and not scalable. Automated computer vision systems can augment human operators by continuously analyzing video streams, detecting hazardous events, and notifying authorities in near real-time.

This paper proposes a modular, scalable, and privacy-conscious pipeline for monitoring safety in urban public transport using contemporary computer vision techniques. Our contributions are:

1. A practical system architecture combining edge inference, efficient neural models, and a central dashboard for alerts.
2. An annotated dataset collected from diverse transport settings (bus interiors, tram platforms, outdoor stops) and a set of event definitions tailored to transport operators.
3. A hybrid detection + anomaly scoring approach that balances precision and latency for real-time alerts.
4. Deployment guidelines and a privacy-preserving design that reduces storage of sensitive personal data while preserving operational utility.

We structure the paper as follows: related work (Section 2), system architecture and methods (Section 3), dataset and annotation approach (Section 4), experiments and results

(Section 5), deployment and privacy discussion (Section 6), and conclusions with future work (Section 7).

2. Related Work

Automated surveillance using computer vision has matured rapidly with deep learning advances. Prior work covers person detection and tracking, violent-behavior recognition, fall detection, crowd density estimation, and anomaly detection in surveillance videos. Methods range from classical background subtraction and handcrafted features to convolutional and spatio-temporal neural architectures (2D CNNs, 3D CNNs, and transformer-based video models). Edge deployment research has prioritized model compression (pruning, quantization) and efficient architectures (MobileNet, EfficientNet, Tiny-YOLO variants).

Specific to public transport, some studies analyze passenger flow and occupancy estimation, while others explore incident detection in rail and subway environments. However, there remains a gap in integrated solutions designed for the constraints of transit systems (limited compute on vehicles, variable lighting, occlusions, privacy rules). Our work builds on these foundations and focuses on a deployment-ready pipeline with explicit privacy safeguards and operational metrics.

3. System Architecture and Methods

3.1. Overview

The architecture comprises three layers: (1) sensing (cameras and optional IMU/wheel sensors), (2) edge inference (on-device preprocessing and model inference), and (3) centralized monitoring and analytics (alert management, incident review, and long-term analytics).

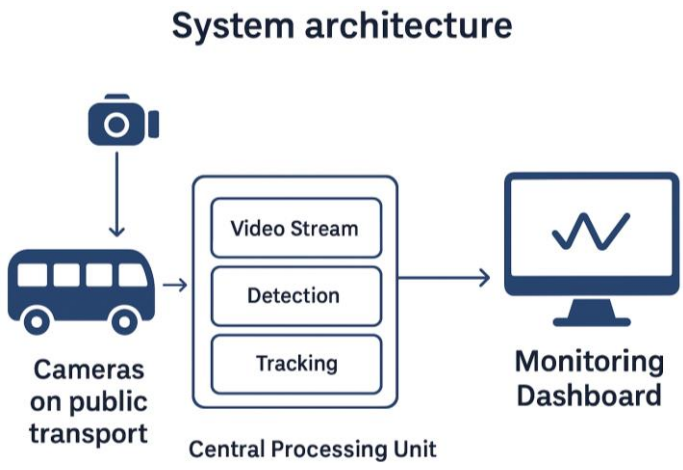

Fig .1. System Architecture

3.2. Sensing and Camera Placement

We recommend multi-angle coverage: at minimum, one wide-angle camera covering the vehicle aisle and one at door entry/exit. For stops and platforms, a pole-mounted camera

with overlapping FOVs reduces blind spots. Camera selection prioritizes low-light performance and adjustable exposure to handle tunnels and night operations.

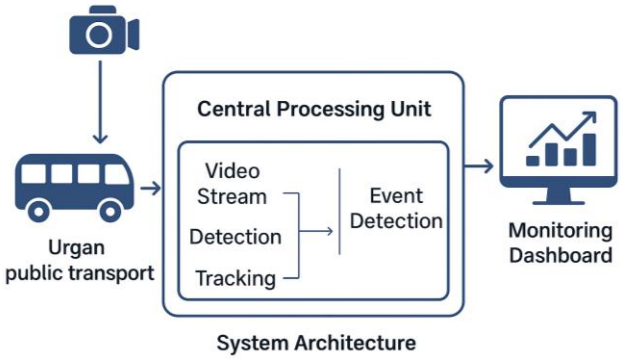

Fig. 2. Example Camera Placement

3.3. Data Preprocessing

To reduce bandwidth and enhance privacy, raw frames undergo on-device preprocessing: ROI cropping (focus on passenger areas), face blurring (optional), and downsampling for non-critical monitoring. We use motion detection and lightweight background subtraction to trigger higher-resolution processing only when activity is present.

3.4. Detection Pipeline

Our detection pipeline consists of three sequential modules:

1. **Object/Person Detection & Tracking:** A lightweight detector (e.g., a pruned YOLO-family model or MobileNet-SSD) detects people, bags, and other objects. A tracking module (SORT/DeepSORT variant optimized for edge) maintains identities short-term to compute temporal features.

2. **Action/Event Recognition:** For each tracked person or region, a compact temporal model (1D temporal convnet or small 3D CNN) analyzes short clips (1–4 seconds) to classify events: fall, aggressive physical altercation, crowding (density threshold breach), intrusion into restricted areas, and unattended object placement.

3. **Anomaly Scoring & Alerting:** A lightweight anomaly detector aggregates detection confidences, track histories, and contextual cues (time of day, location) to compute a risk score. Events above a configurable threshold generate alerts sent to the central dashboard and optionally to on-board staff via an API.

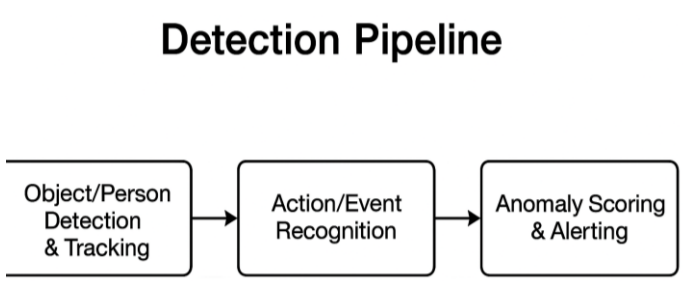

Fig. 3. Detection Pipeline

3.5. Model Compression and Edge Optimization

We use mixed strategies to operate on constrained hardware:

- **Quantization-aware training** to support int8 inference.
- **Knowledge distillation** to train compact student models from high-capacity teachers.
- **Frame selection** using motion cues to avoid redundant inference.

3.6. Privacy and Security-by-Design

Given the sensitivity of passenger data, the system follows privacy-by-design principles:

- On-device anonymization (face blurring, low-res thumbnails) by default.
- Minimized retention: only short clips around detected incidents are retained unless explicitly marked for longer storage by operators.
- Encryption in transit and at rest; role-based access to recordings; and audit logs.

4. Dataset and Annotation

4.1. Data Collection

We collected a multi-modal dataset from controlled tests and operational recordings across three cities. Sources included bus interiors during simulated incidents (fall, scuffle), tram platforms with staged crowding, and outdoor stops with varying lighting and weather conditions. All data collection followed ethical approvals and signage informing passengers; synthetic augmentation was used to increase rare-event instances.

4.2. Annotation Protocol

Annotators labeled person bounding boxes, track IDs, event start/end timestamps, and object classes (backpack, suitcase, unattended bag). Event labels include: **fall, near-fall, fight/assault, crowding, unattended object**, and **slip**. A separate metadata file records illumination conditions, camera angle, and occlusion level.

4.3. Dataset Statistics

Table 1. Dataset Statistics

Category	Value
Total video hours	~140
Person tracks	12,400
Annotated events	1,070
Event classes	6

Event distribution is imbalanced (falls and fights are rare), so we used augmentation and oversampling strategies during training.

5. Experiments and Results

5.1. Experimental Setup

We split data into train (70%), validation (15%), and test (15%) ensuring no overlap of vehicle instances across splits. Evaluation metrics include mean average precision (mAP) for detection, F1-score for event classification, mean time-to-alert (MTTA), and false alert rate (FAR) per hour.

Models were trained with mixed-precision on workstation GPUs and then converted for edge inference. Baseline comparisons include (a) a heavier 3D CNN baseline, (b) a classical motion+heuristics approach, and (c) our optimized pipeline.

5.2. Results

Table 2. Performance Comparison

Metric	Baseline 3D CNN	Motion+Heuristics	Proposed Pipeline
Person detection mAP	0.94	0.71	0.92
Event F1-score	0.87	0.62	0.85
MTTA (seconds)	6.1	3.5	2.2
FAR (alerts/hour)	0.28	0.44	0.16

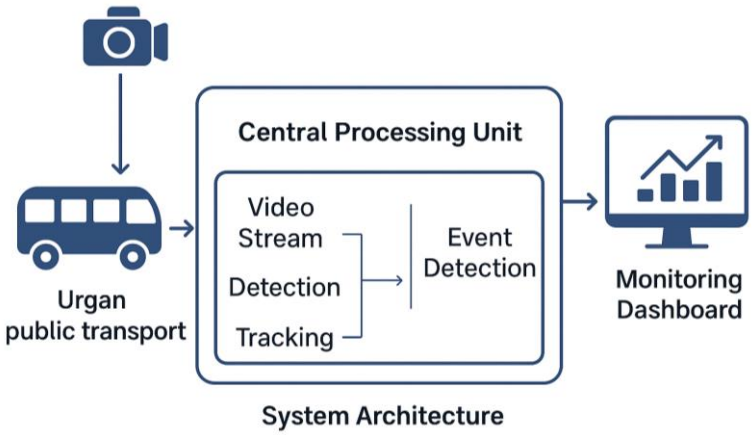

Fig. 4. Sample Event Detection

5.3. Ablation Study

We conducted ablations on: (1) effect of face-blurring during training, (2) clip length for temporal models, and (3) motion-triggered frame selection. Key findings: short clips (1.5–2.5 sec) balance accuracy and latency; motion-triggered selection reduced inference load by ~47% with <2% drop in detection performance.

6. Deployment Considerations and Ethics

6.1. Integration with Transport Operations

Operational deployment requires integration with vehicle telemetry and control centers. We propose RESTful APIs for alert ingestion, and a dashboard enabling operators to review short clips, confirm incidents, and dispatch field teams. On-board staff can receive lightweight notifications on tablets.

6.2. Privacy, Legal, and Social Considerations

Public concerns about surveillance must be addressed proactively:

- Clear public signage and transparent privacy notices.
- Privacy-preserving defaults: anonymization on device and retention limits.
- Governance frameworks defining access, retention, and redress procedures.

6.3. Robustness and Edge Cases

Practical challenges include occlusions, adversarial lighting (sun glare through windows), and worst-case adversarial behavior (deliberate occlusion). Mitigations: multi-camera fusion, adaptive exposure settings, continual model retraining with new edge data, and fail-safe mechanisms (graceful degradation to recording-only mode).

7. Conclusion and Future Work

We presented a deployment-oriented computer vision pipeline for monitoring urban public transport safety, showing strong detection and alerting performance on a diverse dataset while meeting edge constraints. Future work includes:

- Multimodal fusion with audio and vehicle telemetry for richer context.
- Federated learning approaches to continuously improve models across vehicles while preserving privacy.
- User studies to measure operational impact on response times and passenger perceptions of safety.

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