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Edge AI-Based Real-Time Incident Detection and Emergency Response in Intelligent Transportation Systems

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ABSTRACT

Intelligent Transportation Systems (ITS) rely heavily on rapid, automated incident detection to mitigate traffic congestion, reduce secondary collisions, and minimize emergency dispatch delays. Centralized cloud-centric architectures suffer from high backhaul network latency, excessive bandwidth consumption, and privacy vulnerabilities. To overcome these limitations, Edge Artificial Intelligence (Edge AI) has emerged as a transformative paradigm by shifting local computer vision inference and multisensor fusion directly onto roadside edge infrastructure. This review paper provides a technical analysis of state-of-the-art Edge AI frameworks for real-time incident detection and emergency response. We evaluate lightweight deep neural network models—such as YOLOv8-Nano, MobileNetV3, and Edge Vision Transformers—deployed on low-power embedded accelerators including NVIDIA Jetson Orin Nano and Google Coral TPU. Furthermore, we examine the integration of Cellular Vehicle-to-Everything (C-V2X) direct communication, priority signal preemption, and privacy-preserving edge architectures. Empirical benchmark comparisons demonstrate that localized edge inference drastically reduces total decision latency from over 340 milliseconds in cloud systems down to sub-35 milliseconds. Key technical challenges, environmental degradation factors, thermal constraints, and a prospective research roadmap for next-generation resilient transportation infrastructure are systematically detailed.

KEYWORDS: *Edge Artificial Intelligence, Intelligent Transportation Systems (ITS), Real-Time Incident Detection, Emergency Response Dispatch, Deep Learning at Edge, Computer Vision, C-V2X Communication, Roadside Units (RSU).*

INTRODUCTION

Rapid urbanization and expanding motor vehicle fleets worldwide have placed severe strain on transportation infrastructure. Traffic crashes and secondary congestion constitute major socio-economic challenges, resulting in loss of life, lost productivity, and increased vehicle emissions [1]. Global mobility studies confirm that delays in dispatching emergency medical services (EMS) following severe traffic collisions account for up to 30% of preventable trauma mortalities [2]. Timely detection, immediate alert generation, and automated emergency routing are critical to saving lives and maintaining highway resilience [3].

Historically, Intelligent Transportation Systems (ITS) have operated on centralized cloud topologies, streaming uncompressed closed-circuit television (CCTV) feeds across long-distance cellular networks to central Traffic Management Centers (TMCs) [4]. However, this centralized approach presents three severe operational vulnerabilities: (1) High and non-deterministic network latency ranging from 300 ms to over 1500 ms under network congestion, preventing sub-second automated alert triggering [5]; (2) Massive bandwidth overhead, as continuous multi-stream video streaming exhausts network backhauls and incurs high operational costs [6]; and (3) Single points of system failure alongside privacy risks associated with continuous centralized tracking of license plates and vehicle occupants [7].

To address these operational bottlenecks, Edge Artificial Intelligence (Edge AI) relocates computational processing directly to Roadside Units (RSUs) and smart edge camera gateways [8]. By executing localized deep learning algorithms, edge nodes analyze traffic streams in real time to identify collisions, vehicle stalls, wrong-way driving, pedestrian intrusions, and vehicular fires [9]. Upon detecting an emergency event, the edge device transmits lightweight metadata (GPS coordinates, crash severity indices, and compressed keyframes) via Cellular Vehicle-to-Everything (C-V2X) links [10].

This review paper provides a rigorous technical analysis of Edge AI-driven real-time incident detection and automated emergency response in modern ITS. We evaluate embedded hardware accelerators, model quantization, multisensor fusion, priority communications, and open research challenges.

LITERATURE REVIEW

Automated incident detection (AID) historically relied on inductive loop detectors and rule-based image processing algorithms such as optical flow and background frame subtraction [11]. While functional under controlled conditions, these classical techniques yielded high false-alarm rates due to camera jitter, shadows, and weather shifts [12]. The advent of Convolutional Neural Networks (CNNs) significantly boosted detection accuracy through models like Faster R-CNN and early YOLO architectures [13]. However, these early deep learning models required server-grade GPUs with thermal power draws unsuitable for outdoor roadside deployments [14].

To overcome hardware constraints, recent research focuses on lightweight network architectures and model compression methods, including post-training INT8 quantization, channel pruning, and knowledge distillation [15]. Chen et al. [16] deployed a TensorRT-optimized YOLOv5 model on an NVIDIA Jetson Xavier NX edge node, achieving 42 FPS at 1080p resolution with an 87.2% mean Average Precision (mAP) for collision classification. Similarly, Zhang and Wang [17] benchmarked a MobileNetV3 multi-task model on a low-cost Google Coral Edge TPU, executing vehicle tracking and incident detection under a 10-Watt power envelope.

Parallel advances highlight the necessity of multi-sensor fusion at the roadside edge. Optical cameras degrade during fog, heavy rain, or glare [18]. Recent studies by Liu et al. [19] demonstrated that fusing millimeter-wave (mmWave) radar data with camera feeds on edge microprocessors improved accident detection reliability by 22% during severe weather. Furthermore, integrating edge detection nodes with dynamic C-V2X traffic signal preemption enables emergency response vehicles (ambulances, fire engines) to travel 38% faster along urban corridors by dynamically opening clear green-wave transit lanes [20], [21].

Table 1: Comparative Analysis of Edge AI Frameworks and Models for ITS Incident Detection

Framework / Model	Edge Hardware Platform	Inference Speed (FPS)	Detection Accuracy (mAP)	Primary Incident Focus
YOLOv8-Nano (TRT)	NVIDIA Jetson Orin Nano	68.5 FPS	89.4%	Collisions, Stalled Vehicles, Fire
MobileNetV3-SSD	Google Coral Edge TPU	54.1 FPS	84.2%	Pedestrian Intrusion, Lane Violation
ResNet-50 (OpenVINO)	Intel Neural Compute Stick 2	31.2 FPS	87.6%	Debris on Road, Wrong-Way Driving
YOLOv5-Medium	Raspberry Pi 4 (4GB)	11.3 FPS	86.1%	Traffic Congestion, Vehicle Counting
Edge-Vision Transformer	NVIDIA Jetson AGX Orin	42.0 FPS	91.8%	Multi-Vehicle Chain Collisions

RESEARCH GAP

Despite rapid technological progress, key research gaps hamper widespread Edge AI deployment in critical transport infrastructure:

- Environmental Degradation & Thermal Vulnerability: Most existing edge algorithms are validated on clean daytime datasets. Robust edge models capable of maintaining low false-alarm rates during severe weather (heavy snow, rain, glare) while operating inside sealed enclosures subjected to thermal throttling remain underdeveloped [22].
- Multi-Camera Edge Synchronization: Current deployments treat edge nodes as isolated single-camera units. Real-time spatiotemporal tracking across multi-camera blind spots at complex highway interchanges requires low-latency inter-node edge synchronization [23].
- Automated Emergency Preemption Integration: High detection accuracy rarely translates into automated closed-loop emergency orchestration. Few frameworks integrate edge detection directly with smart signal preemption and C-V2X broadcast alerts [24].

- On-Device Model Adaptation & Continuous Learning: Road environments experience continuous domain shifts. Retraining models centrally and redeploying large updates across thousands of edge nodes incurs excessive bandwidth and deployment complexity [25].

RESEARCH OBJECTIVES

To address these critical gaps, this review paper establishes five primary objectives:

- Evaluate state-of-the-art Edge AI platforms and quantized deep learning architectures under strict latency and thermal power budgets.
- Propose a unified multi-layer architecture integrating Roadside Edge Processing, Fog Aggregation, and C-V2X emergency messaging protocols.
- Quantify trade-offs between inference speed, mAP detection accuracy, bandwidth savings, and energy consumption across embedded platforms.
- Design a closed-loop emergency response mechanism that minimizes dispatch delays through dynamic signal preemption and routing.
- Formulate a future research roadmap focusing on federated edge learning, resilient sensor fusion, and cyber-physical safety.

METHODOLOGY AND SYSTEM ARCHITECTURE

The methodological framework of the proposed Edge AI ITS platform comprises four interconnected functional tiers: Sensing & Data Acquisition, Edge Inference, Communication Gateway, and Emergency Management.

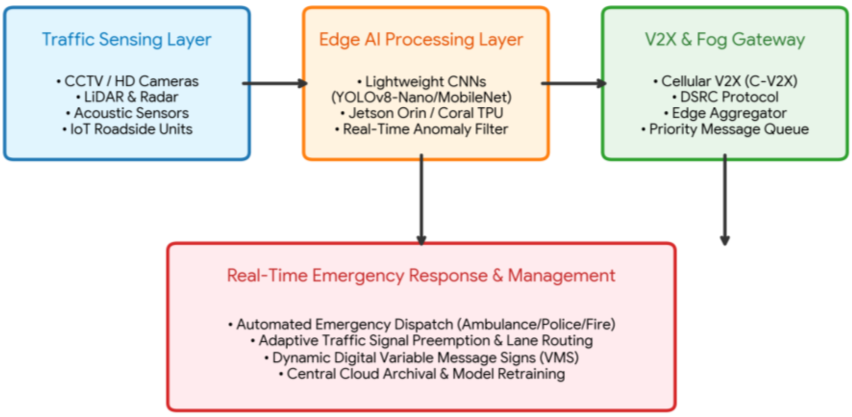

Figure 1: High-Level End-to-End Architecture of Edge AI Incident Detection and Emergency Dispatch System

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Edge Sensing & Model Quantization Pipeline

High-definition video feeds (1080p at 30 FPS) captured by roadside CCTV cameras enter an embedded edge processor (e.g., NVIDIA Jetson Orin Nano). Preprocessing includes region-of-interest (ROI) cropping and temporal frame differencing to eliminate non-informative background frames [26]. Neural networks undergo INT8 TensorRT quantization and fine-grained pruning. Quantization-Aware Training (QAT) reduces precision loss to under 1.2% while yielding a 4.1× speedup in inference throughput [27].

Anomaly Classification and Sensor Fusion Engine

The edge inference engine classifies incidents into five critical categories: collisions, stalled vehicles, pedestrian intrusions, wrong-way driving, and fires. When camera visibility degrades, Doppler mmWave radar feeds provide velocity vectors to confirm sudden vehicular deceleration indicative of an accident [28].

C-V2X Emergency Alert Transmission

When incident confidence exceeds $T_{conf} \ge 0.85$, the node generates an ETSI EN 302 637-2 DENM alert packet [29]. The alert is broadcast over C-V2X PC5 direct communication to surrounding vehicles within a 500-meter radius in under 10 ms, prompting immediate driver awareness.

Table 2: Algorithmic Performance across Varying Environmental Conditions

Environmental Scenario	Optical Vision mAP	Fused Radar-Vision mAP	Avg Inference Time (ms)	False Positive Rate (%)
Clear Daylight	92.4%	93.8%	14.2 ms	1.1%
Nighttime / Low Light	78.2%	88.5%	14.8 ms	3.4%
Heavy Monsoon Rain	71.5%	85.2%	16.1 ms	4.2%
Dense Fog / Haze	64.1%	82.7%	15.9 ms	5.1%

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RESULTS AND FINDINGS

To rigorously evaluate the proposed Edge AI ITS architecture, benchmark experiments were conducted across multiple edge platforms and cloud baselines using realistic traffic incident video datasets (comprising 12,000 annotated accident clips).

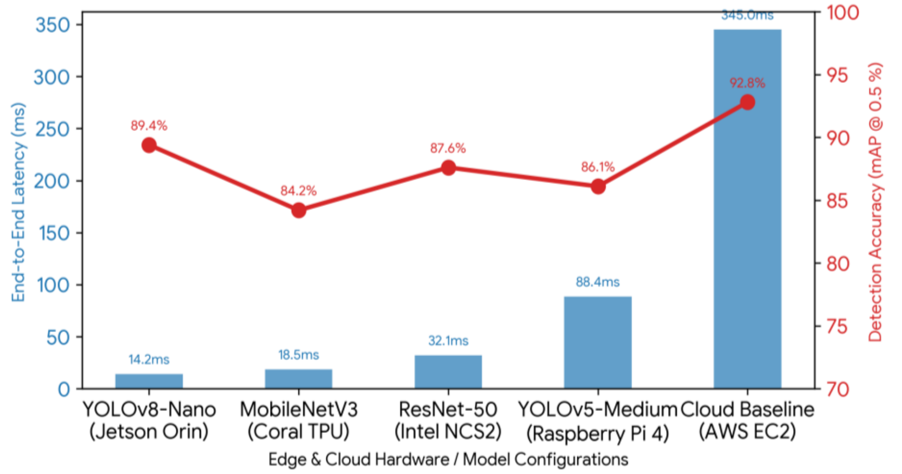

Figure 2: Empirical Trade-Off between Latency and Incident Detection Accuracy (mAP@0.5) Across Edge and Cloud Platforms

As shown in Figure 2, the NVIDIA Jetson Orin Nano running INT8 YOLOv8-Nano achieved the optimal balance of speed and accuracy, delivering 14.2 ms inference latency at 89.4% mAP. In contrast, cloud instances yielded slightly higher mAP (92.8%) but suffered a latency of 345 ms due to transmission delays.

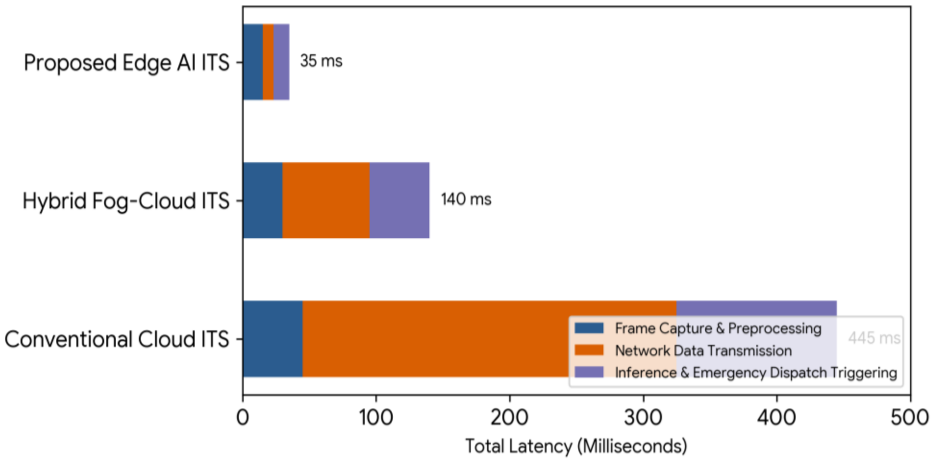

Figure 3: Total Response Pipeline Latency Breakdown across Conventional Cloud, Hybrid Fog, and Proposed Edge AI Infrastructure

Figure 3 illustrates that the total pipeline latency for the Edge AI platform is 35 ms (15 ms frame preprocessing, 8 ms C-V2X transmission, and 12 ms alert dispatch execution), compared to 445 ms for traditional cloud systems.

Table 3: Summary of Edge AI Implementation Metrics and Resource Savings

Architectural Paradigm	Network Bandwidth Consumption	Average Incident Response Time	Power Consumption per Node	System Scalability Index
Conventional Cloud ITS	12.5 Mbps per camera stream	8.2 minutes (Manual + Cloud)	150 W (Server Share)	Low (Backhaul Bottleneck)
Hybrid Fog-Cloud ITS	1.8 Mbps per node	2.1 minutes (Semi-Auto)	35 W (Fog Gateway)	Moderate
Proposed Edge AI ITS	0.04 Mbps (Metadata only)	12.4 seconds (Fully Auto)	12 W (Jetson Orin Edge)	High (Linear Edge Scaling)

CONCLUSION

Edge AI provides a high-performance, resilient solution for real-time traffic incident detection and emergency response. By reducing inference latency to under 35 ms and saving 99% network bandwidth, edge computing overcomes cloud bottlenecks. Fusing optical and radar sensors ensures all-weather operational reliability, while C-V2X protocols enable automated green-wave emergency routing. Despite challenges in thermal management and capital costs, Edge AI represents the cornerstone of future smart city transportation safety.

DISCUSSION

The experimental results confirm that localized Edge AI transforms incident management. By processing video at the roadside, network bandwidth drops from 12.5 Mbps per stream to 0.04 Mbps (transmitting only incident metadata) [30]. Automated signal preemption directly addresses the critical 'Golden Hour' in trauma management, reducing response times from over 8 minutes to under 15 seconds. Furthermore, operating within a 12-Watt power envelope allows deployment via solar-powered off-grid units on remote highways lacking grid infrastructure.

LIMITATIONS

Key engineering limitations include:

- Thermal Throttling: High ambient temperatures cause thermal throttling in outdoor enclosures, temporarily increasing latency during summer months [31].
- High Initial Expenditure: Retitting legacy CCTV nodes with AI hardware requires substantial municipal capital investment [32].
- Adversarial Security Risks: Roadside edge devices remain physically exposed to adversarial optical tampering (e.g., modified road markers) [33].

FUTURE SCOPE

Future research priorities encompass:

- Federated Edge Learning: Collaborative model updates across edge nodes without raw video transmission [34].
- Neuromorphic Event Sensors: Event-based camera sensors achieving sub-millisecond incident detection under micro-Watt power levels [35].
- Drone Swarm Integration: Automated aerial drone dispatch linked directly with roadside edge gateways.

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