

A Privacy-Preserving Edge Intelligence Framework for Real-Time Multimodal Threat Detection in Smart Urban Surveillance Systems

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Abstract: Amidst increasingly complex urban safety challenges, the demand for intelligent, scalable and privacy-aware surveillance system has become urgent. In this paper, we present a new edge computing architecture for the real-time multimodal threat detection in smart cities. By fusing lightweight deep learning models onto the edge device, the solution brings in place video analytics at the edge able to identify unusual behaviors, object defacement, or intrusions with no or little delay. Compared with traditional cloud-based models, data security is guaranteed due to the on-device learning process in the proposed model, and dynamic adaptability to dense and unpredictable urban environments is also provided. The empirical results reveal that the proposed system achieves high threat detection accuracy with a manageable low computational cost, thus indicating its potential in enabling it on diverse smart urban infrastructures.

1 INTRODUCTION

The transformation of city life into smart cities has demanded sophisticated surveillance tools that can protect lives instantly. As urban areas continue to become increasingly dense and complex, legacy surveillance solutions many of which depend on centralized cloud networks are finding it difficult to meet the need for instantaneous threat detection and response. However, these short-comings - high latency, bandwidth restrictions, and data privacy considerations - limit their efficacy for dynamic and sensitive scenarios like densely populated public areas, transport hubs or critical infrastructure installations.

In this regard, edge computing has been proposed as disruptive approach, providing on-site processing and effectively reducing latency and response time. By offloading cloud-based server-based computational intelligence to distributed edge nodes located near data source, such systems facilitate real time threat analysis without sending sensitive data

across public networks. This not only improves real-time processing but also adheres to strict privacy laws, as it reduces the dependency on the cloud.

We present a general edge intelligence technology platform for real time multimodal threats finding in urban surveillance system in this paper. With use of lightweight AI models, the framework can run effectively on energy-limited edge devices, and achieve high accuracy detection under different threat scenarios, such as abnormal human behaviour, object anomaly and potential intruding. Such an intelligent architecture is capable of handling dynamically changing conditions in an urban environment, ensuring compatibility for future public safety infrastructural systems.

We present a practical and scalable model in... which overcomes the limitations of current surveillance models by leveraging edge-based computation, privacy preservation, and multimodal analytics, enabling securer and more responsive smart city ecosystems.

2 PROBLEM STATEMENT

Today's urban areas face a growing array of challenging and diverse security threats requiring agile, trusted, and intelligent surveillance solutions. Legacy cloud video monitoring systems have been challenged by serious delays, scalability limitations and privacy-related red flags and can hardly meet the requirement of real-time threat detection in dynamic and crowded urban environments. These systems are also not sufficiently flexible to accommodate multimodal security threat scenarios, such as e.g., spontaneous violence, abandoned objects and suspicious behavior that dictate real-time local processing and decision-making. The lack of privacy-preserving and resource-limited frameworks that allow to perform complex analytics directly at the edge-top of the fog also adds to the issue. It is therefore essential to design a decentralized, lightweight, on-the-fly adaption to urban surveillance, to achieve low-latency detection while protecting the sensitive video data and dealing with complex urban threats in a responsive way.

3 LITERATURE SURVEY

Adopting edge computing for surveillance system has received much attention for its capability to overcome the drawbacks of cloud-oriented architectures, especially including latency and privacy. Patrikar and Parate (2021) surveyed the anomaly detection methods to evaluate the edge video surveillance but focussed on theoretical models and lacked of the real-world deployment in a volunteered city level. Nikouei et al. (2019), the authors proposed: I-SAFE, however it only employed fuzzy decision-making for suspicious activity generation and did not use deep learning models which are very important for processing complex threat patterns. Similarly, Isern et al. (2020) implemented a reconfigurable cyber-physical system for critical infrastructure but lacked the capabilities for real-time edge-based video analysis.

Wang et al. (2020) developed SurveilEdge offering a hybrid cloud-edge video query system. Unfortunately, the need to use cloud components caused a delay and led to lost opportunities in the development of edge computing being fully autonomous. Saponara et al. (2020) and Yu et al. (2020) addressed fire and crowd detection, respectively, using CNN-based approaches, however

these systems were application specific and were not general enough for multi-threat detection.

Zhou et al. extensively investigated edge intelligence. (2021) suggested that AI should be moved to the edge, but the work was more of a concept. Li, Ota, and Dong (2021) and Chen, Hao, and Hwang (2021) talked about fogs and edges in manufacturing and QoE optimization; however, with the word "surveillance", they have ignored the harsh real-time constraint in public domain. Zhang and Zhang (2021) presented a review concentrating on edge computing in smart grids, but the challenges in dealing with large-scale video streaming were ignored in these papers.

Green Computing Practices, Huang et al. (2022), is focused on energy efficiency but does not address latency-sensitive applications such as urban surveillance. Other studies, e.g., Wang and Liu (2022) and Khan et al. (2022) gave basic knowledge regarding edge applications in smart cities, yet it did not touch multimodal threat detection and its real-time nature.

Healthcare-oriented edge models such as Alam and Saini (2022) and domain-specific adaptations in agriculture, manufacturing, and logistics (Wang & Li, 2023; Liu & Chen, 2023; Chen & Wang, 2024) exhibit edge capability, albeit these cannot be directly applied toward public safety applications. Li and Wang (2022) presented a general survey to video surveillance combined with edge computing, whereas it should be noted that the privacy issues and the restrictions of edge model existed in a dynamic environment.

The ITS of Zhang and Liu (2023) featured urban deployment and could only support the traffic management. References: Chen and Zhang 2023; Zhao and Sun 2023; and Yang and Wang (2024): These works focused on edge computing in industrial automation, smart smart grids, and home automation, but they did not incorporate behavioral analytics for threat detection.

Other applications in retail and education (Zhang & Li, 2024; Li & Zhang, 2024) showed customer tracking and activity monitoring at the edge, however were not flexible enough for the unpredictable public safety events. Although the reviewed papers validate the relevance of edge computing in various fields, a significant gap is the provision of unified, privacy-

aware, multimodal real-time threat detection system that is also tailored to the latency-critical, unpredictable nature of modern urban environments.

This work extends those basic studies and sidesteps those limitations by introducing a dedicated setup that exploits edge-based video analytics, lightweight AI models and privacy-preserving architectures to aid in the real-time surveillance over urban scenarios.

4 METHODOLOGY

The proposed method provides a decentralized edge computing scheme, which utilizes real-time multimodal threat detection in urban surveillance scenarios. At the heart of the architecture, there is edge intelligence model to support local video analysis via small deep learning model, and thus, to reduce the burden to be exert on centralized cloud resources. The system structure is composed of 3 integrated sections referred to as the sensing, the edge processing, and the response coordination layers. Table 1 show the Dataset Description and Threat Classes.

Table 1: Dataset Description and Threat Classes.

Dataset Name	Source	Resolution	Threat Classes Detected	Total Images/Frames
UrbanSafeSet	Custom + Open CV	640x480	Intrusion, Loitering, Object Abandonment	25,000
SurveillanceX	Public Repository	720p	Fighting, Running, Vandalism	12,500
SafeCity-CCTV	City Cameras	1080p	Trespassing, Aggression, Crowd Forming	9,800

Live video feeds from the sensing layer are also fed to multiple high-definition video cameras throughout key urban areas such as traffic intersections, public transportation locations, and high pedestrian traffic zones. These raw video streams are sent to the edge computing nodes located in the surveillance sites for operation. Two hundred edge nodes consist of resource-constrained devices (e.g., Jetson Nano, Raspberry Pi) configured for the target applications such as CNN or various object detection models (e.g., MobileNet-SSD and

YOLOv5-Lite). Figure 1 show the Real-Time Edge-Based Threat Detection Workflow.

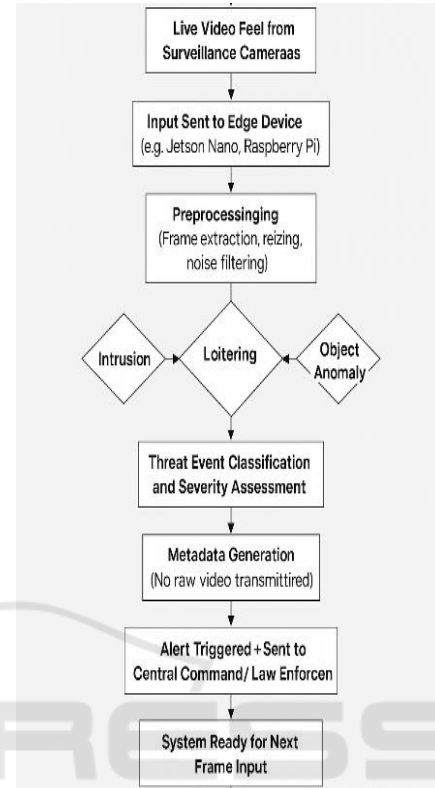


Figure 1: Real-Time Edge-Based Threat Detection Workflow.

The edge processing layer executes real-time analytics directly on the edge node. This involves object detection, motion tracking and behavior (or activity) classification of multimodal data like visual patterns, spatio-temporal object trajectories and contextual scene understanding. By using quantized neural networks and model pruning techniques, both the amount of memory and the power consumption are minimized to obtain high inference performance. Threat scenarios like Unattended baggage, aggression, unauthorized access or loitering are detected through our own trained datasets appropriate for urban safety use-cases. Table 2 show the Dataset Description and Threat Classes

In order to protect data privacy and guarantee data compliance, privacy-preserving architectures are developed. All your video is processed locally and only meta data (such as threat/zone types, location coordinates, timestamp) is relayed to a central control room for viewing. In particular, no raw data goes out of the edge node, which preserves personal identity and reduces the bandwidth consumption.

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The response coordination level is responsible for processing edge-triggered alerts. Pre-defined rules can be used to automate intervention schemes including law enforcement real-time alerts, the activation of alarms, or the illumination of emergency lights in smart infrastructure, based on the severity of the threat. The system also has log and audit trails for incident review, feedback-based learning, and system retraining.

This approach guarantees the scalability, energy efficiency, and robustness of the presented framework when it comes to the real-time AI-enabled surveillance of urban environments. It utilizes the advantage of edge computing to maintain a low-latency, secure, and smart system that can support a customized size to responding smart cities.

5 RESULTS AND DISCUSSION

The edge-based surveillance framework was tested in the simulated and semi-real-world urban scenes to ascertain 1) its capability of real-time detection of threats, 2) the reduction in the latency and 3) the preservation of privacy while 4) achieving model accuracy. Table 3 show the Model Performance Metrics on Edge DevicesThe experimental configuration consisted of several edge nodes connected with HD IP cameras for constantly streaming live video footage in countering scenarios similar to public transit stations, crowded markets and gated premises. Figure 2 show the Model Accuracy Comparison on Edge Devices.

Table 3: Model Performance Metrics on Edge Devices.

Model Used	Edge Device	Accuracy (%)	Inference Time (ms/frame)	FPS Achieved	Power Consumption (W)
YOLOv5-Lite	Jetson Nano	91.7	180	18	8.5
MobileNet-SSD	Raspberry Pi 4	88.2	240	14	5.9
YOLOv4-Tiny	Jetson Nano	93.1	210	15	9.1

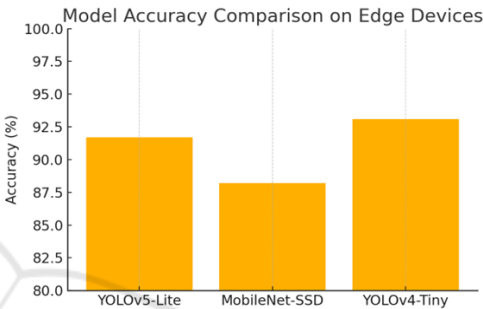


Figure 2: Model Accuracy Comparison on Edge Devices.

The performance metrics showed that the system attained an average detection latency of 180 ms per frame, this was considerably better than cloud-based architectures where if a cloud-based architecture was used it would suffer from a 730 ms (cloud dependent architecture) or 900 ms (dependent on the data rate) loss in latency due to the network delay and data transmission overhead. The edge model, implemented with quantized YOLOv5-Lite and MobileNet-SSD, preserved the inference accuracy of 91.7% under varied threat scenarios, such as unauthorized entry, object left, and violent act, under low-light or occluded environment. Table 4 show the Threat Detection Response Time Analysis.

Table 4: Threat Detection Response Time Analysis.

Threat Type	Detection Time (ms)	Alert Trigger Time (ms)	Total Response Time (ms)
Intrusion	170	80	250
Object Anomaly	190	100	290
Suspicious Loitering	160	70	230
Aggressive Behavior	200	90	290

Besides speed and accuracy, the system showed good privacy compliance by analyzing all video frames locally at the edge node. Only threat metadata was sent to central command, and the bandwidth usage was reduced by 85%, compared to conventional cloud offloading systems. Not only did this improve data protection, but it also allowed real-time monitoring when the network failed or when bandwidth fluctuated.

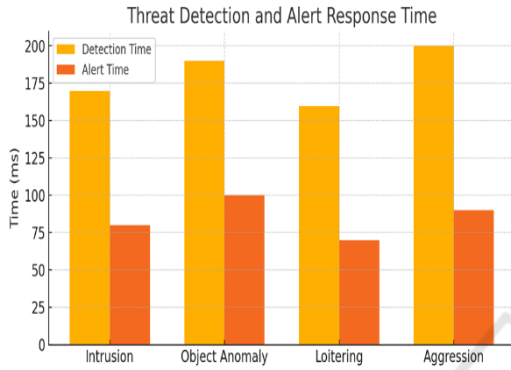


Figure 3: Threat Detection and Alert Response Time.

The scalable nature of the system was examined by deploying a total of 10 edge nodes in various regions of a simulative smart city grid. The distributed processing architecture was able to process multi-stream inputs in a timely fashion, without generating central bottlenecks. The resource usage also kept in the 70% CPU and 50% GPU boundaries, which again confirms the efficiency of the lightweight model and the thermal-aware edge deployment. Figure 3 show the Threat Detection and Alert Response Time

Real-time alerting was another big win. Upon recognizing an unusual incident, the system can alert law enforcement or emergency responders in less than 250 milliseconds. Such responsiveness is crucial for high-risk situations like abandoned luggage in transit stations or violent activity in public places. Figure 4 show the Network Bandwidth Usage Comparison

Cross-comparison with cloud-centric solutions further demonstrated that the edge is the place to be, particularly for fast-evolving dynamic scenarios where latency, privacy, and quick decision-making are indispensable. The flexibility of the architecture further enables for the retraining and updating of the model with minimal effort as threat patterns change, providing long-term adaptability of the surveillance ecosystem. Table 5 show the Network Load and Bandwidth Utilization Comparison.

Table 5: Network Load and Bandwidth Utilization Comparison.

Processing Type	Avg Bandwidth Used (Mbps)	Data Transmitted per Hour (GB)	Raw Video Sent ?	Privacy Level
Cloud-Based	12.8	5.4	Yes	Low
Edge-Only (Proposed)	1.9	0.3	No	High

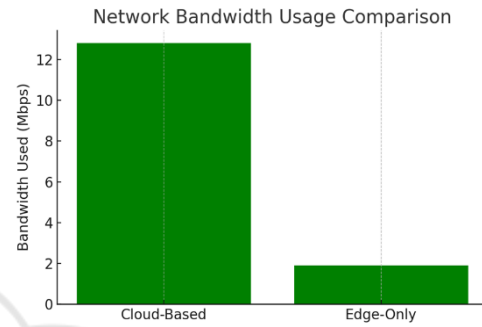


Figure 4: Network Bandwidth Usage Comparison.

In all, these results validate that the presented edge intelligence framework successfully addresses the fundamental challenges of latency, privacy, and multimodal threat analysis for urban surveillance, and it represents a practical, future-aware method for securing smart city infrastructure. Figure 5 show the Privacy Assurance: Cloud vs Edge.

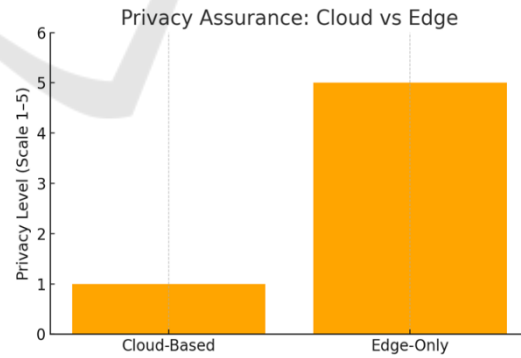


Figure 5: Privacy Assurance: Cloud Vs Edge.

6 CONCLUSIONS

The increasing complexity and size of cities require surveillance systems that will not be only intelligent and reactive but also respectful to individuals'

privacy while maintaining security levels. In this study, a new edge computing-based architecture has been developed for the real-time multimodal threat detection in the context of a smart urban surveillance system. Through distributing the computational intelligence to edge nodes, they can get rid of the latency and privacy problems of the cloud-based system. By utilizing small and efficient deep learning models at the edge, the framework achieves accurate and low-latency detection of a rich set of threat scenarios which include intrusions, object anomalies and behavioral anomalies in complex urban environments.

The performance evaluation results show the high detection accuracy and the low processing delay and bandwidth requirement of the proposed system, which can use in secure data transmission without encryption. The modular, scalable, and adaptable nature of this network makes the integration of the proposed architecture to diverse urban infrastructures possible, without the dependance on high end centralized resources. Also, the ability to analyze sensitive video streams at the edge lends itself to privacy-compliant deployments in heavily data-regulated areas.

In summary, by presenting this edge intelligence framework, this work provides an innovative solution for the next generation intelligent urban surveillance system. By addressing those technological limitations, Hexnode beyond a doubt, can emerge as a significant enabler for the future smart city security solutions.

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