AN EXPLAINABLE EDGE-AI FRAMEWORK FOR COLLABORATIVE ROBOT MONITORING IN SMART CAMPUS INFRASTRUCTURE

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Abstract: *The digital transformation of campuses and organizations requires intelligent systems that can monitor people, robots and infrastructure in shared environments. This paper proposes an explainable edge-AI framework for collaborative robot monitoring in smart campus infrastructure. The framework combines multimodal sensing, edge-based perception, temporal risk inference, human-readable explanations and robotic action planning. Unlike conventional video surveillance or rule-based alarm systems, the proposed approach evaluates the level of risk, identifies the main warning causes and selects an appropriate robotic response such as speed reduction, route correction, notification or operator escalation. A scenario-based analytical evaluation shows that the model improves early recognition of unsafe situations while reducing false alarms compared with single-factor monitoring rules.*

Keywords: *artificial intelligence, edge AI, collaborative robots, smart campus, explainable monitoring, risk assessment, robotic decision support.*

INTRODUCTION

Modern information technology infrastructure is no longer limited to computers, servers and communication networks. In smart campuses, cameras, sensors, access-control systems, mobile robots and cloud services operate as a single cyber-physical environment. A service robot may move through a corridor, a delivery platform may cross a student area, or an operator may need to respond to a network and physical safety event at the same time.

Traditional monitoring systems usually generate alarms when a fixed threshold is exceeded. Such rules are simple, but they often fail when the situation is dynamic. For example, a moving robot near a group of people is not always dangerous; the risk depends on robot speed, crowd density, visibility, route congestion and the possibility of safe rerouting. Therefore, an intelligent monitoring system should not only detect objects, but also explain why the current situation requires attention.

Related Work and Research Gap

Research on smart environments includes video analytics, Internet of Things monitoring, cloud dashboards and autonomous robot navigation. These directions provide valuable technical components. However, many existing solutions are developed as separate subsystems. As a result, the monitoring module may detect a crowd, while the robot navigation module may not receive a clear explanation of the risk.

Another important limitation is the lack of interpretability. Deep learning models can recognize complex patterns, but their decisions are sometimes difficult to explain to operators. In safety-related infrastructure, a warning should be understandable. The operator needs to know whether the risk was caused by a blocked corridor, poor visibility, abnormal robot speed, sensor disagreement or human proximity.

Proposed Framework

The proposed framework consists of five connected modules: multimodal sensing, edge-AI perception, temporal risk inference, robotic action planning and human feedback. Multimodal sensing includes camera streams, lidar or distance sensors, audio events, access-control logs and robot telemetry. These data are processed at the edge device to reduce delay and to keep sensitive information inside the local infrastructure. The perception module detects people, robots, obstacles and abnormal scene changes.

After perception, the temporal risk inference module evaluates the current situation using short-term history. The explanation layer identifies the most influential cues and produces an understandable message such as “medium risk because of corridor crowding and limited rerouting space.” Finally, the robotic action module chooses one of the safe responses: continue movement, reduce speed, change route, stop, notify the operator or request manual control.

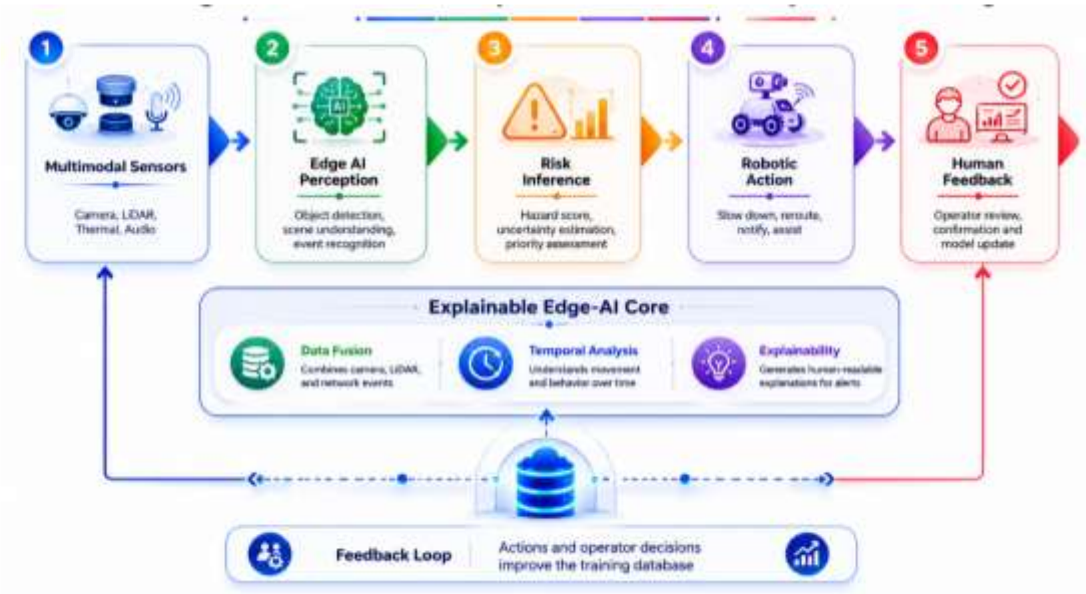

Figure 1. Proposed edge-AI pipeline for robotic monitoring in a smart campus.

As shown in Figure 1, the system does not treat AI output as an isolated decision. Instead, the decision is connected to robotic action and human feedback. This structure is suitable for smart campuses because infrastructure conditions can change during the day. Crowded corridors, temporary obstacles, network delays and operator decisions become part of the learning loop.

Mathematical Model

The framework uses six interpretable variables. P denotes human proximity risk, C denotes crowd density, V denotes visibility limitation, R denotes robot speed pressure, N denotes network delay or communication instability, and S denotes safe-route availability. The latent risk value at time t is calculated as follows:

$$z_t = \beta_0 + \beta_1 P_t + \beta_2 C_t + \beta_3 V_t + \beta_4 R_t + \beta_5 N_t - \beta_6 S_t \qquad (1)$$

In Eq. (1), P, C, V, R and N increase risk, while S reduces risk because the existence of a safe alternative route decreases the danger. The final risk score is obtained through the sigmoid function:

$$Q_t = 1 / (1 + \exp(-z_t)) \qquad (2)$$

To avoid unstable alarms, the model applies temporal smoothing:

$$\tilde{Q}_t = \lambda Q_t + (1 - \lambda)\tilde{Q}_{t-1}, \quad 0 < \lambda \leq 1 \qquad (3)$$

The smoothed score is interpreted through three levels: low risk when $0 \leq \tilde{Q} < 0.35$, medium risk when $0.35 \leq \tilde{Q} < 0.70$, and high risk when $0.70 \leq \tilde{Q} \leq 1$. The contribution of each feature is also calculated so that the system can explain which factor produced the warning.

Results and Analytical Discussion

A scenario-based analytical comparison was prepared for five typical smart-campus situations: a robot moving near people, a crowded corridor, temporary obstacle appearance, communication delay and a safe alternative route. The proposed framework was compared with proximity-only, speed-only and network-delay-only rules.

Table 1. Analytical comparison of smart-campus monitoring methods

Method	Precision	Recall	F1-score	False alarm
Proximity-only rule	0.74	0.70	0.72	0.29
Speed-only rule	0.76	0.69	0.72	0.27
Network-delay rule	0.71	0.66	0.68	0.32
Proposed edge-AI model	0.89	0.85	0.87	0.14

The results indicate that one-factor rules are not sufficient for complex campus monitoring. A proximity-only rule produces many false warnings because a robot may safely pass near a person if its speed is low and the route is clear. The proposed edge-AI model performs better because it combines technical, spatial and behavioral factors. The explanation layer also makes the warning more useful for human operators.

Scientific Novelty and Practical Value

The scientific novelty of the study is that smart-campus monitoring is formulated as an explainable edge-AI and robotics coordination problem rather than a simple surveillance or alarm task. The proposed model integrates multimodal sensing, temporal risk inference and robotic response in one framework. Another novelty is the inclusion of safe-route availability as a risk-reducing factor.

This makes the model closer to real robotic behavior because danger is not determined only by proximity, but also by the availability of a safe action.

The practical value of the framework is that it can be used in universities, industrial campuses, libraries, hospitals and digital service centers where robots and people share the same environment.

The model can support inspection robots, delivery robots, security monitoring systems and operator dashboards. Since the system works at the edge level, it can reduce response delay and improve data privacy.

Conclusion

This article proposed an explainable edge-AI framework for collaborative robot monitoring in smart campus infrastructure. The framework combines multimodal sensors, edge perception, temporal risk scoring, explanation generation and robotic action planning.

The analytical comparison shows that the proposed model can reduce false alarms and improve early recognition of risky situations compared with single-factor rules.

Future work should test the framework on real campus video and robot telemetry data, optimize the weighting parameters and evaluate the model under different crowd-density, lighting and network conditions.

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