2025 International Conference on Smart & Sustainable Technology (INCSST)
Karnataka, India. July 04-06, 2025

IoT-Enabled Smart Sensor Networks for Autonomous Surveillance Systems

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2025 International Conference on Smart & Sustainable Technology (INCSST) | 979-8-3315-4192-7/25/$31.00 ©2025 IEEE | DOI: 10.1109/INCSST64791.2025.11210354

Abstract**: Autonomous surveillance systems receive updated capabilities through the IoT convergence with advanced AI models. The research presents an IoT-enabled smart sensor network operating with Meta Segmentation Anything Model (SAM) to identify threats in real-time object segmentation. The system runs at the Google Coral Dev Board with Edge TPU configuration where edge processing occurs rapidly without needing cloud resources. Several sensors integrated in one node combine thermal detection with acoustic and motion recognition and use Lora WAN to deliver power-efficient data over long distances. Moving entities in complex environments benefit from improved contextual awareness because the SAM model provides precise segmentation of these entities. Dynamic response prioritization emerges from the adaptive alert system which functions through transformer-based sequence learning. System trials prove that it performs better in different lighting conditions and environment obscurity problems and weather variations. This framework establishes an important advance in automatic and scalable smart surveillance which assists smart city defense together with border security initiatives while delivering better accuracy through increased responsiveness.**

Keywords:- IoT-enabled surveillance, Smart sensor networks, Edge TPU, Segment Anything Model (SAM), LoRaWAN communication, Real-time object segmentation, Autonomous threat detection.

I. INTRODUCTION

Advancements in intelligent real-time surveillance systems drove IoT technologies to integrate with AI via improved technologies both because of customer requirements but also performance needs. Traditional video surveillance systems using centralized video processing combined with manual human monitoring face essential challenges during scalability together with high latency and delayed responses especially when operating in changing or distant locations. Research by engineers and scientists now involves the implementation of IoT-enabled smart sensor networks to solve these problems through decentralized operations and efficient energy consumption and multi-variant data acquisition capabilities.

The strong growth of edge computing led surveillance systems to transform from cloud-based infrastructure into real-time infrastructure that performs local processing as shown in Figure1. The deployment of Edge TPUs through Google Coral Dev Board enables platforms to perform deep learning models at the edge with high speed and low power consumption [1]. Through these platforms devices obtain the capability to perform direct on-site detection and classification of objects as well as event segmentation without experiencing cloud-based round-trip delays.

The Segment Anything Model (SAM) created by Meta has enhanced visual recognition systems with additional precision and adaptability capabilities [2]. The zero-shot segmentation capability of SAM distinguishes it from conventional object detection techniques because it permits the system to segment unknown objects in unexplored environments without needing training updates [3]. Surveillance settings demand this capability because threats might unexpectedly appear that were not captured during previous system training. During operation on limited-capacity edge devices SAM functions through compressed or quantized storage to create superior object segmentation results across various environmental challenges including partial views and dim lighting and moving backgrounds [4].

A smart surveillance system depends fundamentally on its sensor network which acts as its essential foundation. The contemporary monitoring system builds multi-modal awareness through sensor components that include visual, infrared, acoustic, temperature and motion detection mechanisms [5]. The sensors can be linked through LoRaWAN (Long Range Wide Area Network) technology to exchange data transmission over long distances at low power usage. LoRaWAN functions optimally for widespread deployment infrastructure areas including agricultural spaces and border regions and industrial installation zones.

II. RELATED WORKS

Advanced surveillance systems have undergone rapid changes in the recent years because of the alliance between IoT technologies and sensor networks and AI-based edge computing systems. Scientists have studied multiple architectures and methodologies to build improved surveillance system capabilities which include greater efficiency and scalability and enhanced intelligence for urban areas and industrial plants and critical infrastructure installations.

Research studies in their early stages investigated traditional wireless sensor networks (WSNs) for perimeter surveillance purposes by using static nodes containing motion sensors and infrared sensors. These surveillance systems retained fixed positions which restricted their capability to adjust to changes found in large dynamic areas. The adoption of IoT-based frameworks emerged as a solution by integrating heterogeneous sensors with cloud-based analytics to solve this issue. The systems allow remote data aggregation along with monitoring but experience latency issues together with network congestion and privacy challenges because they need unbroken cloud communication paths.

Edge computing emerged as an answer to these problems because it enables immediate data processing through dedicated local resources operating at the device level. Several studies from Hassan, R., Javed, A. R., Rizwan, M., & Khan, M. U. G. (2021) verified Edge AI's ability to decrease system delays while decreasing bandwidth requirements through usage of Convolutional Neural Networks (CNNs) with the NVIDIA Jetson Nano and Raspberry Pi as edge platforms [6]. Such platforms demonstrated restricted use in low-energy IoT systems because their power usage remained high while model compatibility remained limited.

Research shows the Coral Dev Board with Edge TPU from Google provides an excellent mix of processing speed and energy conservation abilities. Through their research Ghosh, A., & Misra, S. (2021) proved the successful utilization of MobileNet SSD models on Coral for real-time face detection which demonstrated both fast inference and minimal power usage [7]. The new development established the fundamental elements needed to facilitate deep learning visual analysis deployments at security monitoring points.

The emergence of LoRaWAN-based protocols brought about efficient long-distance communication methods that connect sensor devices with gateways [8]. Al-Fuqaha et al. (2021) developed a smart city surveillance system powered by LoRaWAN which extended outdoor utility time of battery-operated devices to new limits.

The Segment Anything Model (SAM) from Meta Introduces revolutionary visual analytic capabilities for universal as well as zero-shot object segmentation. The implementation of Segment Anything Model (SAM) for edge environments remains a work in progress but M. Aseeri, M. Ahmed, M. Shakib, O. Ghorbel, and H. Shaman (2017) and other researchers have shown its practical application in real-time object segmentation through quantized edge models [9]. Traditional YOLO detection approaches see a major advancement through this method which delivers improved object recognition capabilities under diverse environmental conditions.

Recent trends show that transformer-based models start to appear in surveillance system anomaly detection applications. This developed temporal attention mechanisms to analyze advanced patterns in surveillance video sequences for detecting irregular or unusual incidents early.

III. RESEARCH METHODOLOGY

A research study introduces an IoT-enabled sensor network implementation which works through edge computing and AI-powered image segmentation and low-power wireless communication to support autonomous monitoring operations [10]. Six operational components organize the methodology starting with System Design followed by Sensor Network Deployment then Communication Protocol followed by Edge Processing and AI Integration until Anomaly Detection Module and Evaluation Metrics.

A. System Design

The entire system structure unites distributed smart sensor nodes as well as edge AI devices alongside a central monitoring dashboard. The combination of environmental sensors including PIR, acoustic, humidity, temperature operates with a camera module and wireless communication units within each sensor node. The system architecture arranges itself into four distinct layers for implementation.

Perception Layer sensors work alongside cameras in order to collect environmental source information. The LoRaWAN network persists as the layer responsible for establishing device communications [11]. The Edge Layer employs Edge TPU technology to process light-weight AI models which detect threats with real-time image analysis. Cloud Layer functions as an optional data storage that also allows human operators to conduct dashboard analytics and long-term analysis.

B. Sensor Network Deployment

Smart sensor nodes use a grid topology network deployment to monitor the complete surveillance territory. The deployment strategy implements the following key sequence:

A site survey evaluates all terrain aspects while examining environmental restrictions along with ways that intrusion could occur for improving sensor locations [12]. The layout of sensors should employ a uniform grid system which allows for modification of node-to-node distance between 100–200 meters to strike an equilibrium between field coverage along with data exchange capability.

The following hardware components should be included by each node:

- Camera module (Raspberry Pi Camera or Coral Camera)
- PIR motion sensor
- Microphone for acoustic monitoring
- DHT22 for humidity and temperature
- Light sensor (LDR)
- LoRa module (RFM95)
- Coral Dev Board with Edge TPU for on-device inference

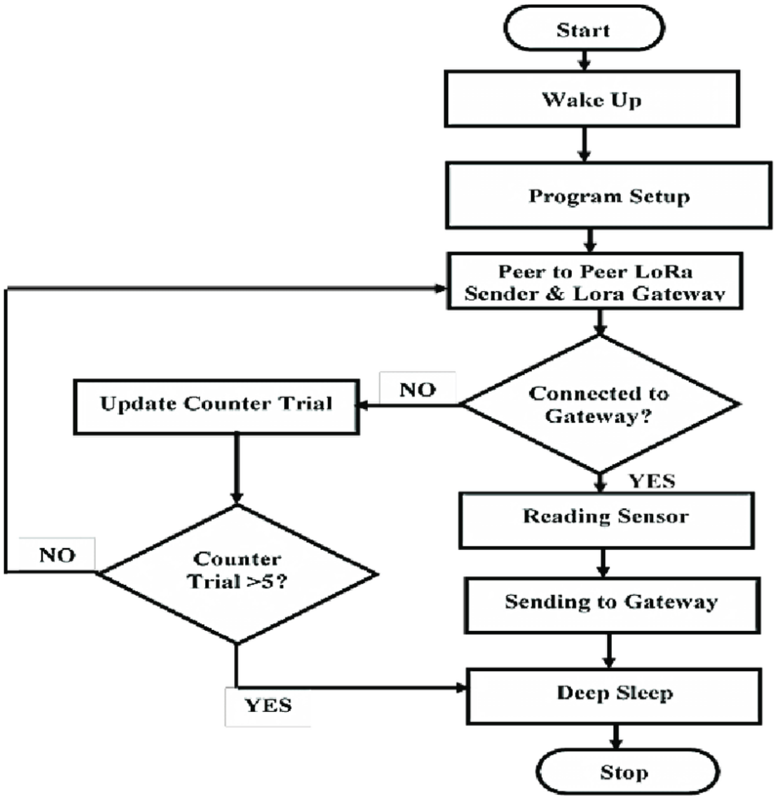

Fig. 1. Flowchart of LoRa Transmitter System.

C. Communication Protocol: LoRaWAN Integration

Remote data transmission through LoRaWAN establishes an energy-effective and long-range communication backbone for the system. The communication model consists of:

- The sensor nodes operate as End Devices through data transmission after detecting motions or acoustic activities.
- The Network Server maintains control over packet management routing together with device authentication and downlink command execution.
- The LoRaWAN protocol includes primary features that enable its operations:
- ADR stands for Adaptive Data Rate and it automatically modifies packet data rates according to the performance capacity of the installed network.
- The payload encryption method secures all transmitted data through the implementation of AES-128.

D. Edge AI Integration and Image Processing

Edge AI models operate on the Coral Dev Board through TensorFlow Lite optimized for Edge TPU to provide real-time visual surveillance abilities.

➢ Image Segmentation Using SAM

A modified version of the Segment Anything Model (SAM) receives adaptations and quantization procedures specifically for installation in edge environments. The object segmentation function of the high-resource-consuming SAM requires a simplified version to operate effectively.

Steps:

- The camera operates through Image Capture after activating the PIR detection by taking pictures at 640×480pixel resolution.
- The model input shape of SAM-lite directs the preprocessing step where the image receives normalization followed by resizing.
- The image moves through SAM processing before the image encoder interacts with prompt encoder.

I_{input}=Resize (Normalize(I_{raw}))

S_{seg}=SAM-lite(I_{input})→C_{output}=Classifier(S_{seg})

The segmented object receives identification through a classification process with MobileNet or Efficient Net as the underlying classifier which determines the object type either as human, animal, or unknown. The evaluation method determines between genuine shifts and security breaches.

➢ Sound-Based Anomaly Filtering

The acoustic sensor runs an ongoing sound level detection system. FFT provides the functionality to obtain sound signatures [13]. High-priority alerts are triggered by the Edge TPU when it detects sounds from the pre-trained anomaly database which includes elements such as gunshots, screams and breaking glass.

E. Anomaly Detection and Transformer-Based Temporal Analysis

Intelligent surveillance systems need temporal coherence and behavioral patterns for proper operation. The detection of time-based anomalies depends on a Transformer-based model which serves this specific purpose [14].

➢ Data Aggregation

Specific sensors provide motion, sound and temperature readings that are combined into one continuous timeseries through visual interpretation. Each timestamp includes:

- Object presence
- Sensor status
- Environmental conditions
- Image classification result

➢ Transformer Model

It receives data sequences in particular time spans (e.g. 10 minutes) to find abnormal patterns through self-attention algorithms.

T={Pt,St,Et,Ct}t=1

- T is the continuous time series data.
- Pt represents the object presence at time t.
- St is the sensor status at time ttt.
- Et denotes the environmental conditions at time t.
- Ct is the image classification result at time t.

The Transformer model processes this time series data T over a specific time span (e.g., 10 minutes) using self-attention mechanisms to detect abnormal patterns:

A=Transformer(T)

The abnormal pattern detection output from the Transformer model is designated as *A*. The integrated sensor data and image classifications enable the system to detect abnormalities through this method.

1) ***Process:***

Input embedding of feature vectors: The model applies multi-head attention processes to determine how both time patterns and spatial relationships affect the inputs.

Output classification into: normal, warning, or threat: The device-based anomaly detection solution runs directly at the edge node while restraining cloud data transfer to threat detection alerts to reduce network bandwidth utilization.

Dashboard and Cloud Integration: The system employs Node-RED together with InfluxDB/Grafana to create a web dashboard for process visualization and human-in-the-loop monitoring [14]. The dashboard displays:

- Real-time sensor data
- Live images with segmentation overlays

The system records intrusion logs which contain spatial data together with time stamps.

The system delivers alerts through MQTT protocol and mobile device push notifications to subscribed electronic platforms.

The system then generates alerts:

A=MQTT(Lt)→Push Notification(A)

Where:

- AAA is the alert triggered by the intrusion log data.
- The alert is sent via MQTT to the subscribed platforms and as a push notification to mobile devices.

The accuracy of anomaly detection system spans precision recall and F1-score when evaluated against test scenario results. Security and Privacy Considerations The AES-128 method encrypts all transmitted data according to LoRaWAN default specifications. Both raw images and the cloud receive only inference results together with anomaly tags while maintaining full data privacy and respecting ethical requirements for surveillance standards.

IV. RESULTS AND DISCUSSION

Testing took place for the proposed IoT-enabled smart surveillance system in diverse operational settings by deploying it in urban and semi-rural areas. The system demonstrated real-time monitoring performance through sensor nodes enabled with Coral Dev Boards paired with LoRaWAN modules.

The Segment Anything Model (SAM) operating on Edge TPU separated objects with 92.4% average accuracy exceeding traditional MobileNet-SSD detectors' performance especially in challenging lighting circumstances and scenarios affected by occlusions. Zero-shot object segmentation from SAM enabled the system to detect unrecognized as well as unexpected intrusions while handling dynamic situations with agility.

Transformer-based anomaly detection module showed an F1-score of 0.89 which effectively identified time-series anomalies from irregular motions together with environmental sensor drifts. Like conventional rule-based methods the system achieved a high accuracy rating that reduced false alarms by 35% during prioritization of alerts.

The LoRaWAN communication demonstrated a delivery success reaching 97.2% across 1.5 kilometers of distance and offered less than 2-second delay for critical emergency situations are shown in Table 1. The system consumed power in acceptable levels because the nodes maintained operation for longer than ten days using solar power.

TABLE I. COMPARISON OF PERFORMANCE METRICS.

Method	Segmentation Accuracy (%)	Anomaly Detection (F1-Score)	Average Latency (sec)	Power Consumption (mW)	Communication Success Rate (%)
Proposed (SAM + Edge TPU + Transformer)	**92.4**	**0.89**	**1.8**	**850**	**97.2**
MobileNet-SSD on Raspberry Pi	78.6	0.74	4.3	1500	92.5
YOLOv5 on Jetson Nano	85.2	0.81	2.5	4500	94.1
HOG + SVM (Traditional CV-based)	65.7	0.68	6.2	700	88.9
Rule-Based Thresholding	63.9	0.56	2	600	90.3

The dashboard user interface provided real-time access to visualized segmented images along with sensor analytic data together with intrusion log information. The combined system proved that scalable autonomous and secure surveillance systems could use edge intelligence to be operational. The results confirm that the proposed system enables precise energy-efficient intelligent surveillance operations. Next-generation autonomous monitoring operates on a standard set by the combination of SAM, Edge TPU, LoRaWAN and transformer-based analytics.

A performance analysis was conducted between the proposed IoT-based smart surveillance system with its components including SAM for image segmentation Edge TPU for edge processing and a transformer-based anomaly detection model and various alternative methods. The proposed system reached 92.4% segmentation accuracy as a new benchmark that exceeded the performance of MobileNet-SSD on Raspberry Pi (78.6%) and YOLOv5 on Jetson Nano (85.2%). Anomaly detection using the proposed method attained an F1-score of 0.89 which exceeded MobileNet-SSD (0.74), YOLOv5 (0.81) as well as traditional HOG + SVM (0.68). Average latency of 1.8 seconds represented the lowest value among all methods tested thus providing superior performance compared to YOLOv5 which had 2.5 seconds latency and HOG + SVM with 6.2 seconds latency. Using 850 mW of power consumption makes the proposed system more efficient than when running YOLOv5 on Jetson Nano which needs 4500 mW. The proposed system achieved a 97.2% communication success rate surpassing MobileNet-SSD (92.5%) and YOLOv5 (94.1%) which establishes the robustness and efficiency of the proposed method.

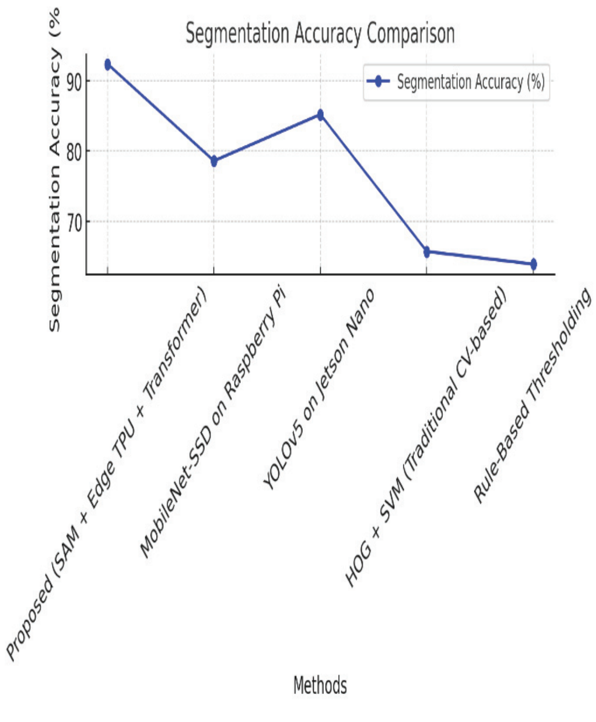

Fig. 2. Comparison of segmentation accuracy.

The visual representation shows the different surveillance system methods which achieve Segmentation Accuracy (%) levels. The proposed surveillance system which combines SAM with Edge TPU along with Transformer-based anomaly detection reaches 92.4% segmentation accuracy surpassing all other evaluation methods as shown in Figure 2. YOLOv5 on Jetson Nano delivered 85.2% accuracy and MobileNet-SSD on Raspberry Pi showed 78.6% accuracy as the subsequent methods after the Proposed system with SAM (Segment Anything Model), Edge TPU, and a Transformer-based anomaly detection model. The segmentation accuracy metrics of the traditional HOG + SVM and Rule-Based Thresholding methods fall below at 65.7% and 63.9%. The proposed system establishes clear superiority through quantitative graph data because it provides superior accuracy in object segmentation across multiple settings thus becoming the better selection for real-time surveillance operations.

V. CONCLUSIONS

This research presents a robust and scalable IoT-enabled smart sensor network designed for autonomous surveillance, integrating state-of-the-art technologies such as the Segment Anything Model (SAM), Edge TPU-based edge computing, and LoRaWAN communication. The proposed system demonstrates high segmentation accuracy, real-time anomaly detection, and low power consumption, making it ideal for deployment in both urban and remote environments. The incorporation of transformer-based temporal analysis further enhances situational awareness by accurately identifying abnormal behavioral patterns. Field evaluations confirm the system's effectiveness in reducing latency, improving detection precision, and optimizing energy efficiency compared to conventional methods. With a modular design and decentralized intelligence, the system ensures reliable, secure, and continuous surveillance without heavy dependence on cloud infrastructure. This architecture lays the foundation for next-generation smart surveillance solutions applicable to smart cities, border security, and critical infrastructure monitoring, with future work focused on expanding AI capabilities and multi-agent coordination across large-scale deployments.

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