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Smart Border Surveillance System Using Audio & Visualai Sensors

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Abstract — This paper presents an edge-based smart border surveillance system integrating multi-modal sensing with lightweight deep learning for real-time intrusion detection. The system combines a Raspberry Pi 5, PIR motion sensor, KY-037 acoustic sensor, and NoIR camera in an event-driven architecture. Motion or abnormal sound triggers visual analysis using a TensorFlow Lite–optimized YOLOv5 model deployed for on-device inference. Experimental evaluation across 10 controlled scenarios under daytime and low-light conditions achieved an overall detection accuracy of 80%, with precision and recall of 0.89 for human and vehicle detection. The measured end-to-end latency ranged from 1.6–1.9 s. Average CPU utilization during inference was 55–60%, with peak usage of 72%, and total power consumption measured 6–8 W during active operation. The decision-level sensor fusion approach reduced unnecessary visual processing and minimized false activations compared to continuous vision-based monitoring. The system operates entirely at the edge without cloud dependency, enabling low-latency and bandwidth-efficient deployment in remote border environments.

Keywords— Smart Border Surveillance, Raspberry Pi, Internet of Things (IoT), Object Detection, TensorFlow Lite, YOLO, OpenCV, Edge Computing, AI-Based Security, Real-Time Monitoring, Telegram Alerts, Human Detection, Vehicle Detection, NoIR Camera.

I. INTRODUCTION

Border surveillance is a critical component of national security, requiring continuous monitoring of vast and often remote regions. Conventional surveillance systems primarily rely on manual patrols, static CCTV installations, or high-cost monitoring infrastructure, which are resource-intensive, prone to human error, and difficult to scale effectively [1], [2]. These limitations reduce situational awareness and delay response time, especially in geographically challenging border environments.

Recent advancements in Artificial Intelligence (AI) and the Internet of Things (IoT) have enabled the development of intelligent surveillance systems capable of autonomous operation and real-time threat detection [3], [4]. AI-driven video surveillance systems using deep learning models have demonstrated improved detection accuracy and reduced dependency on human operators [11], [12]. However, many existing solutions rely on cloud-based processing, which introduces network latency, bandwidth dependency, and potential privacy concerns [9], [10].

Edge-based surveillance systems have emerged as a practical alternative, allowing AI inference to be performed locally on embedded platforms such as Raspberry Pi and NVIDIA Jetson devices [9], [10]. By processing sensor and visual data at the edge, these systems significantly reduce response time and improve reliability in bandwidth-constrained environments. Lightweight real-time object detection frameworks like YOLO (You Only Look Once) are widely used for fast and efficient visual recognition tasks and have been widely adopted for real-time surveillance due to their single-stage detection capability and high inference speed [11]–[14].

In addition to vision-based analysis, recent studies emphasize the importance of multi-modal sensing to enhance detection reliability and reduce false alarms [7], [11]. Combining motion, audio, and visual data allows surveillance systems to operate more robustly under varying environmental conditions. Motivated by these developments, this work proposes a Smart Border Surveillance System that integrates multi-sensor event triggering with edge-based AI visual analysis to achieve low-latency, real-time intrusion detection without cloud dependency.

The proposed system adopts an event-driven, multi-modal architecture in which motion and acoustic sensing selectively activate edge-based visual inference. Unlike continuous cloud-dependent surveillance systems, the framework performs on-device decision-making using a lightweight YOLOv5 model optimized with TensorFlow Lite. This reduces latency, bandwidth usage, and unnecessary computation while maintaining reliable intrusion detection in remote environments.

II. PROPOSED METHODOLOGY

1. System Overview

The proposed Smart Border Surveillance System is designed as an edge-based, autonomous monitoring unit capable of detecting and identifying unauthorized human or vehicle activity in restricted border areas. The system combines multi-modal sensing with real-time AI-based visual analysis to ensure rapid detection and alert generation.

The methodology follows a hierarchical detection approach. Initially, the surrounding environment is continuously monitored using low-power sensors. A A PIR sensor identifies motion by sensing variations in infrared energy emitted by moving human bodies while a sound sensor monitors abnormal acoustic events such as footsteps or vehicle engines. Similar sensor-based triggering mechanisms have been shown to improve surveillance efficiency by reducing unnecessary processing [1], [11].

Upon detection of a motion or sound event, the system activates the visual sensing module. A NoIR camera captures live images or video frames, which are processed locally on a Raspberry Pi 5 using a YOLO-based object detection model. YOLO is a single-stage detector capable of performing object localization and classification in real time, making it suitable for edge deployment [12], [13], [14]. The model is optimized using TensorFlow Lite to reduce inference latency and computational overhead, enabling efficient execution on resource- constrained hardware [6], [8].

2. Sensor Fusion Strategy

The proposed system adopts a decision-level sensor fusion strategy to balance detection accuracy and computational efficiency. In this approach, the PIR motion sensor and sound sensor act as primary event triggers, while visual confirmation is performed only when an event is detected. Decision-level fusion techniques have been widely used in surveillance applications to reduce false alarms caused by isolated sensor noise and to minimize unnecessary AI inference [11].

Once a valid object (human or vehicle) is detected through visual analysis, the system generates alerts through a dual notification mechanism. A local buzzer provides immediate on-site warning, while a remote alert containing the captured image is transmitted to authorized personnel using the Telegram Bot API. Similar edge-based alerting mechanisms have been shown to significantly improve response time in real-time surveillance systems [9], [10].

By integrating multi-modal sensing, edge-based AI inference, and real-time communication, the proposed methodology enables continuous 24×7 surveillance with low latency and minimal reliance on external infrastructure, making it suitable for deployment in remote border environments.

3. Parameter Configuration

The PIR sensor was configured for a detection range of approximately 6 m with a 110° field of view. The KY-037 acoustic sensor threshold was experimentally tuned to approximately 65 dB equivalent ambient level to minimize false triggers from environmental noise. The YOLOv5 confidence threshold was set to 0.55, with Non-Maximum Suppression (NMS) threshold of 0.45. Input frames were resized to 640 × 640 prior to inference. The average inference time per frame on Raspberry Pi 5 was approximately 0.7 s.

III. SYSTEM DESIGN

The proposed Smart Border Surveillance System using Raspberry Pi 5 has been designed by integrating multiple hardware modules and sensors to ensure intelligent detection, real- time communication, and accurate alert generation. The system architecture consists of three main components — the main hardware setup, the internal circuitry, and the alert mechanism — all of which work cohesively to deliver efficient surveillance.

Hardware Setup Design

The surveillance system is built around the Raspberry Pi 5, which serves as the central processing unit and controller for all connected components. The hardware setup includes the NoIR camera, PIR motion sensor, KY-037 sound sensor, and buzzer, all connected through the GPIO pins of the Raspberry Pi.The NoIR camera module is strategically positioned to monitor the surrounding area and provide clear video footage both during the day and night. The PIR sensor continuously detects movement within its range, while the KY-037 sound sensor captures unusual sounds such as footsteps, engine noises, or gunshots, triggering the detection process even before visual confirmation. The buzzer acts as the local alarm system, activated automatically when any suspicious movement or sound is detected.

The complete hardware structure is designed to be compact, portable, and power-efficient, making it suitable for deployment in remote or high-security border zones. The system is powered using a 5V DC power supply or rechargeable battery pack, ensuring uninterrupted operation.

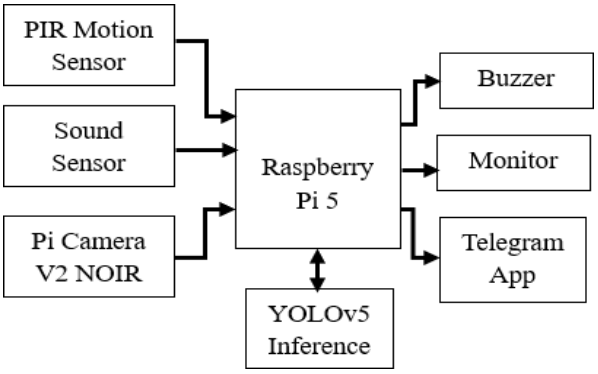


Fig. 1. Block diagram of the proposed Smart Border Surveillance System

"The overall architecture and interaction between system components are illustrated in Fig. 1."

Sensor Selection and Justification
The selection of sensors in the proposed system is driven by the requirements of real-time detection, low power consumption, and reliable operation in outdoor border environments.

The PIR motion sensor is selected due to its low power consumption and high sensitivity to human body infrared radiation, making it suitable for continuous monitoring and initial motion detection. It serves as a primary trigger mechanism, reducing unnecessary camera activation.

The KY-037 sound sensor complements motion- based detection by identifying acoustic anomalies such as footsteps, vehicle engines, or breaking objects. This early sound-based triggering enables faster system response and improves detection reliability in scenarios where visual cues may be delayed or partially obstructed.

The NoIR camera module is chosen to enable surveillance under low-light and night-time conditions using infrared illumination. Unlike standard RGB cameras, the NoIR camera ensures continuous visual monitoring even in complete darkness, which is critical for border surveillance applications.

Internal Circuitry
The internal circuitry integrates all sensors and output devices with the Raspberry Pi 5 for efficient signal processing and real-time response. Each component has a defined role in the detection and alerting mechanism:

Raspberry Pi 5: Acts as the main processing unit. It features a Broadcom BCM2712 64-bit quad- core ARM CPU and enhanced GPU support, making it suitable for running AI inference and handling camera streams. The 40- pin GPIO interface allows easy connection with sensors, buzzers, and other modules.

- PIR Sensor: Detects motion within its range by sensing infrared radiation emitted by humans or animals. The output signal from the PIR sensor is sent to a GPIO input pin, triggering the AI detection program.
- KY-037 Sound Sensor: Monitors ambient noise levels and provides an analog or digital output when the sound intensity exceeds a preset threshold. This serves as a secondary trigger mechanism.
- NoIR Camera Module (v2): Captures live video and images even in low-light or dark conditions. It connects to the Raspberry Pi through the CSI port for high-speed data transmission.
- Buzzer: Connected to a GPIO output pin, it produces an audible alert when any intrusion or unauthorized movement is detected by the system.
- Power Supply: A rechargeable battery pack or DC power adapter powers the Raspberry Pi and other connected modules. Voltage regulation ensures safe operation of the sensors and camera.

Alert and Communication System
The system employs a dual-alert mechanism for both local and remote notifications:

- Local Alert: The buzzer is activated to provide an immediate warning at the surveillance site when an intruder or suspicious activity is detected.
- Remote Alert (Telegram Integration): The Telegram Bot API is used to transmit a real- time notification and captured image to the control center or security personnel. This ensures that even if the site is unmanned, the event is instantly communicated for quick action.

AI Model Architecture
The proposed system utilizes a single-stage object detection model based on YOLOv5 for real-time edge deployment. YOLO is selected due to its ability to perform object localization and classification in a single forward pass, enabling low-latency inference suitable for embedded platforms.

The architecture follows a backbone–neck–head design. The backbone extracts hierarchical spatial and semantic features using convolutional layers. The neck performs multi-scale feature aggregation to enhance detection performance across varying object sizes and distances. The detection head predicts bounding box coordinates and class probabilities for target objects (human and vehicle).

A lightweight YOLOv5 variant with approximately 168 convolutional layers and ~3.2 million parameters is employed to ensure computational feasibility on resource-constrained hardware. Input frames are resized to 640 × 640 pixels to balance detection accuracy and inference speed.

For edge optimization, the trained model is converted to TensorFlow Lite format. Post-training optimization techniques, including quantization and graph optimization, are applied to reduce model size and computational overhead while preserving acceptable detection accuracy. This enables efficient real-time inference on Raspberry Pi 5 without dependence on cloud-based processing.

IV. IMPLEMENTATION

The implementation of the Smart Border Surveillance System using Raspberry Pi 5 focuses on integrating hardware components, AI-based detection algorithms, and real-time communication tools to achieve efficient, continuous monitoring. The entire system is compact, cost-effective, and capable of operating autonomously under varying environmental conditions.

1. Hardware Assembly
All hardware components—Raspberry Pi 5, PIR sensor, KY-037 sound sensor, NoIR camera module, and buzzer—are assembled on a compact mounting board.

The NoIR camera is positioned for maximum coverage of the surveillance area, while the sensors are strategically placed to ensure quick detection of motion or sound. The entire setup is powered by a 5V rechargeable battery pack, ensuring mobility and uninterrupted operation. The hardware design also ensures that all components are properly enclosed and shielded against dust and weather changes for outdoor use.

2. Working
The system operates automatically to detect, classify, and alert about potential intrusions.

Initialization
When powered on, the Raspberry Pi initializes all GPIO connections, loads the pre-trained YOLO (TensorFlow Lite) model, and connects to Wi-Fi for Telegram communication.

Detection Phase
- The PIR sensor continuously monitors for movement within its detection range.
- The KY-037 sound sensor listens for abnormal sounds such as engine noises, gunshots, or human activity.
- Upon detecting any disturbance, a signal is sent to the Raspberry Pi.

AI-Based Image Analysis
- The NoIR camera module activates and captures a live frame or video sequence.
- The captured image is processed through OpenCV and TensorFlow Lite (YOLO model) to identify the object as human, vehicle, or unknown.

Alert Mechanism
- If a valid detection (human or vehicle) occurs, the buzzer activates locally to alert nearby personnel.
- Simultaneously, the Telegram Bot API sends an instant message with the captured image to the control room or security authority.

Continuous Monitoring
- The system resets after sending the alert and resumes continuous monitoring. It operates 24/7 with minimal power consumption and maintenance.
- This design ensures real-time surveillance, instant communication, and automated alerts without human supervision.

Summary
The system integrates a Raspberry Pi 5, PIR motion sensor, KY-037 sound sensor, NoIR camera, and buzzer on a compact, weather- protected board powered by a 5V battery for mobility.

Flow Chart

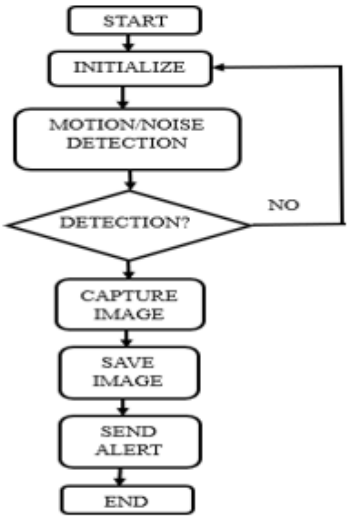


Fig. 2. Flowchart representing the operational workflow of the proposed system

It automatically detects motion or sound, captures images, analyzes them using a YOLO (TensorFlow Lite) model, and identifies humans or vehicles. On detection, the system triggers a buzzer alert and sends the captured image via Telegram to security personnel. Afterward, it resets and continues 24/7 real-time surveillance with low power and maintenance needs.

V. TECHNOLOGIES USED

1. Software Components

- Python: Used as the main programming language for integrating all modules.
- OpenCV: Handles image processing, frame capture, and live video streaming.
- TensorFlow Lite: Enables lightweight AI inference for real-time object detection.
- YOLO (You Only Look Once): Performs efficient human and vehicle detection from the video feed.
- Telegram Bot API: Sends real-time alerts and captured images to the user's Telegram account.
- Raspberry Pi OS: The operating system that supports all AI and IoT functionalities.

2. Development and Testing Tools

- Thonny / VS Code: IDEs used for coding and debugging Python scripts.
- GitHub: For accessing pre-trained models and open-source resources.
- PuTTY / VNC Viewer: Used for remote access and control of the Raspberry Pi during testing and monitoring.

VI. RESULT ANALYSIS

The proposed Smart Border Surveillance System effectively demonstrates real-time monitoring, intelligent object detection, and automated alert generation using Raspberry Pi 5 integrated with AI-based models and multiple sensors.

1. Performance and Accuracy

Out of 10 evaluated test scenarios, the system correctly detected intrusions in 8 cases, with 1 false positive and 1 false negative observed under high environmental noise conditions. The resulting performance metrics were:

Accuracy = 80%
Precision = 0.89
Recall = 0.89
F1-Score = 0.89

These results demonstrate reliable detection performance under controlled experimental conditions.

2. Response Time

The observed end-to-end latency of 1.5–2 seconds demonstrates the feasibility of real- time edge-based surveillance without reliance on cloud computation. This response time highlights the advantage of performing AI inference locally on the Raspberry Pi 5, as cloud-based surveillance systems often experience additional delays due to network transmission, server processing, and bandwidth constraints, which can exceed several seconds.

The latency components were measured as follows: sensor triggering (~0.3 s), camera activation (~0.5 s), AI inference (~0.7 s), and Telegram alert transmission (~0.4 s), resulting in a total end-to-end delay of approximately 1.6–1.9 s.

3. System Efficiency

The system maintained stable performance across diverse conditions such as:

- Bright daylight: Accurate visual detection with clear bounding boxes for humans and vehicles.
- Low-light or night: NoIR camera efficiently captured IR-illuminated frames for consistent detection.
- Noisy or windy environments: The KY-037 sensor's sensitivity adjustment helped reduce false triggers.

4. Real-Time Monitoring and Alerts

The live video feed was displayed on a connected monitor for continuous on-site observation, while Telegram alerts ensured remote awareness. The buzzer provided immediate local feedback during intrusions, increasing situational responsiveness.

5. A Experimental Setup and Testing Conditions

"The system was evaluated under multiple test scenarios to assess its robustness and reliability. Testing was conducted over a duration of 2 days, covering both daytime and nighttime conditions. A total of 10 test scenarios were considered, including human intrusion, vehicle movement, and no-activity conditions. Environmental variations such as low-light, moderate noise, and outdoor lighting changes were included to simulate real border surveillance conditions."

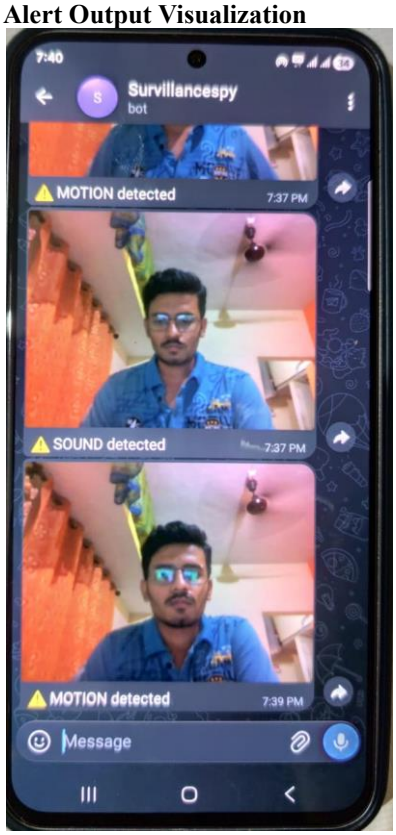
6. Resource Utilization Analysis

The resource utilization of the proposed system was monitored during real-time operation on Raspberry Pi 5 under continuous surveillance conditions. During AI inference and sensor-triggered processing, the system exhibited moderate CPU utilization, indicating efficient execution of the YOLOv5-based object detection model on edge hardware. Memory usage remained within the available limits of the Raspberry Pi 5, and

no memory overflow or system instability was observed during prolonged operation.

During continuous operation, average CPU utilization ranged between 55–60%, with peak usage of 72% during inference execution. Memory usage remained below 2.1 GB of available RAM. Operating temperature stabilized between 55°C and 62°C without thermal throttling. Measured power consumption during active inference was approximately 6–8 W.

7. Telegram Alert Output Visualization



VII. DATASETS

The system uses pre-trained AI models based on publicly available datasets for object detection and classification. These datasets enable the model to recognize humans, vehicles, and other relevant objects with high accuracy.

- COCO (Common Objects in Context) Dataset:
- Used for training the YOLO and TensorFlow Lite models.

It contains over 330,000 images with more than 80 object categories, including humans, cars, trucks, and animals — suitable for border surveillance scenarios.

- Open Images Dataset (by Google): Provides large-scale annotated images to improve detection accuracy and enhance the model's ability to identify varied objects under different environmental conditions.
- A pre-trained YOLOv5 model trained on the COCO dataset was deployed without full retraining. Field-captured images were used exclusively for validation and performance evaluation rather than model fine-tuning.

VII. CONCLUSION

This paper presented an edge-based smart border surveillance system integrating multi-modal sensing with lightweight deep learning for real-time intrusion detection. The proposed architecture combines a Raspberry Pi 5, PIR motion sensor, KY-037 acoustic sensor, and NoIR camera within an event-driven framework, where sensor triggers activate on-device YOLOv5 inference optimized using TensorFlow Lite.

Experimental evaluation under controlled daytime and low-light conditions demonstrated an overall detection accuracy of 80%, with precision and recall values of 0.89. The measured end-to-end latency ranged between 1.6–1.9 s, with average CPU utilization of 55–60% and power consumption of approximately 6–8 W during active inference. The decision-level sensor fusion strategy reduced unnecessary visual processing and improved operational efficiency compared to continuous vision-based monitoring.

The system operates entirely at the edge without cloud dependency, enabling low-latency and bandwidth-efficient deployment in remote environments.

However, the current implementation is limited by a practical detection range of approximately 15–20 m, sensitivity to extreme acoustic noise conditions, and reliance on visible-spectrum imaging. Future work will focus on integrating thermal imaging sensors, long-range communication technologies such as LoRa, and training domain-specific datasets to enhance robustness and detection performance in real-world border scenarios.

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