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Development of an Embedded Deep Learning Accelerator for Real-Time Perimeter Security

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Abstract
Modern perimeter security systems require intelligent, autonomous, and low-latency monitoring to prevent unauthorized access in restricted environments. This paper presents the development of an embedded deep learning accelerator for real-time perimeter security by integrating computer vision intelligence with FPGA-assisted control. A Raspberry Pi equipped with a camera module captures live video streams and processes them using the YOLO (You Only Look Once) deep learning algorithm for accurate human detection. Upon detecting an unauthorized individual, the Raspberry Pi generates control signals and communicates with an SLG47910 Renesas FPGA through GPIO interfaces. The FPGA acts as a deterministic hardware accelerator to execute response logic such as alert triggering and system control with minimal latency. The hybrid architecture combines software-based intelligence with hardware reliability to achieve fast, scalable, and autonomous surveillance. The proposed system is suitable for military perimeters, restricted industrial zones, and smart border monitoring applications.

Keywords: *Deep Learning, YOLO, FPGA, Perimeter Security, Embedded System, Smart Surveillance, Raspberry Pi*

1. Introduction
Perimeter security plays a critical role in protecting military bases, industrial plants, borders, and restricted facilities. Conventional surveillance systems depend largely on passive cameras and human operators, which introduce delays, fatigue, and reduced response efficiency. With the growth of artificial intelligence, vision-based autonomous monitoring systems have become viable alternatives to manual surveillance. Deep learning based object detection algorithms such as YOLO enable real-time identification of humans and objects with high accuracy. However, software-only implementations often suffer from latency when deployed on embedded platforms. To overcome this limitation, hardware assistance using FPGA technology is introduced. FPGAs provide parallel execution, deterministic timing, and reconfigurable logic, making them ideal for accelerating control and response mechanisms in real-time systems. This work proposes an embedded deep learning accelerator architecture for perimeter security by integrating Raspberry Pi based vision intelligence with SLG47910 Renesas FPGA assisted control. The Raspberry Pi performs high-level detection using YOLO, while the FPGA handles low-level response logic with minimal delay. This hybrid model ensures fast detection, reliable control, and automated response, improving the overall effectiveness of perimeter surveillance systems.

1.1. Background of Deep Learning in Surveillance
Deep learning has transformed surveillance by enabling automatic feature extraction and classification directly from images. Unlike traditional image processing methods, convolutional neural networks (CNNs) learn spatial patterns and contextual information effectively. YOLO is a single-stage detector that processes the entire image in one pass, making it suitable for real-time applications such as defense surveillance, traffic

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monitoring, and security systems.

2. Literature Review

Recent advances in perimeter security heavily rely on deep learning based vision systems for automatic intrusion detection. Redmon et al. (2016) introduced the YOLO framework, a unified real-time object detection approach that performs detection in a single stage, enabling high-speed and accurate human recognition suitable for surveillance environments [1]. Its capability to process entire images in one pass makes it ideal for embedded and real- time security applications. Liang et al. (2022) proposed Edge YOLO, which integrates edge and cloud cooperation to achieve real-time intelligent object detection with reduced latency and improved scalability [2]. Their work demonstrates that deploying YOLO models on edge devices significantly improves responsiveness in surveillance and transportation systems, which directly supports the use of Raspberry Pi based vision processing in perimeter security. To further optimize deep learning for embedded platforms, Dong et al. (2022) presented PG-YOLO, a lightweight object detection model designed for edge and IoT devices [3]. Their results show improved inference speed and reduced computational complexity while maintaining detection accuracy, making such models suitable for resource-constrained embedded security systems. Hardware acceleration using FPGA has also been widely explored to overcome latency limitations of software-only approaches. Montgomerie-Corcoran et al. (2023) introduced SATAY, a streaming architecture tool flow for accelerating YOLO models on FPGA devices [4]. Their research highlights how FPGA parallelism can significantly reduce inference time and power consumption for real-time object detection. Additionally, Amin and Hasan (2024) demonstrated an FPGA-based real-time object detection and classification system using YOLO for edge computing applications [5]. Their work confirms that combining deep learning with FPGA assistance improves determinism, throughput, and system reliability, which motivates the hybrid Raspberry Pi–FPGA architecture proposed in this work for perimeter security.

3. Methodology

The proposed system follows a layered approach consisting of vision acquisition, deep learning processing, communication, and hardware assisted response. The camera continuously captures frames which are transferred to the Raspberry Pi. The YOLO model processes each frame and identifies humans with bounding boxes and confidence scores. If the detection exceeds a predefined threshold, a control signal is generated. This signal is transmitted via GPIO to the SLG47910 FPGA. The FPGA executes parallel logic to trigger alerts and manage response actions. The separation of computation and control improves speed, reliability, and scalability of the system.

3.1. System Architecture

The architecture consists of three layers:

- Vision Layer – Camera module for image acquisition.
- Processing Layer – Raspberry Pi running YOLO deep learning model.
- Control Layer – SLG47910 FPGA executing deterministic response logic.

3.2. Hardware Components

- Raspberry Pi
- Camera Module
- SLG47910 Renesas FPGA
- GPIO Interface
- Alert Module (Buzzer / Indicator)
- Power Supply

3.3. Software Components

- Linux OS
- Python
- OpenCV
- YOLO Framework
- FPGA Configuration Tools (Table 1)

Table 1 The Experimental Configuration Parameters Used for Evaluation

Parameter	Value
Frame rate	20 FPS
GPIO voltage	3.3V
FPGA clock	50 MHZ
Camera resolution	640x480
YOLO Model	YOLOv5-Nano

3.4. Block Diagram

Figures 1 and 2 are used to represent the system architecture and processing flow.

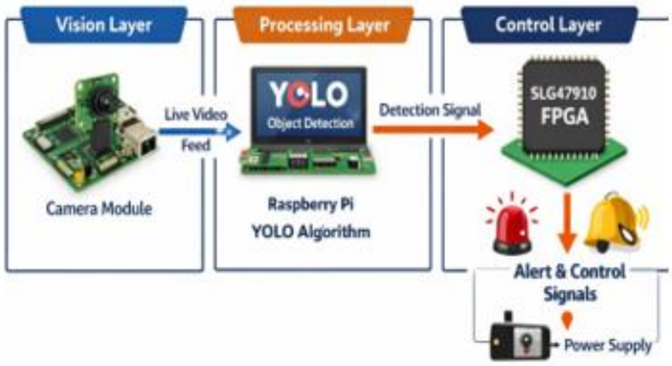

Figure 1 Block Diagram of Embedded Perimeter Security System

4. Results and Discussion

4.1. Results

The implemented system was tested under controlled indoor and outdoor environments. The YOLO model achieved reliable human detection with real-time processing at approximately 18–22 FPS on the Raspberry Pi. The FPGA response latency was measured to be in the microsecond range, ensuring immediate alert generation after detection. The system successfully identified unauthorized human presence and generated control signals without manual intervention. The hybrid design reduced processing delay compared to purely software-based systems.

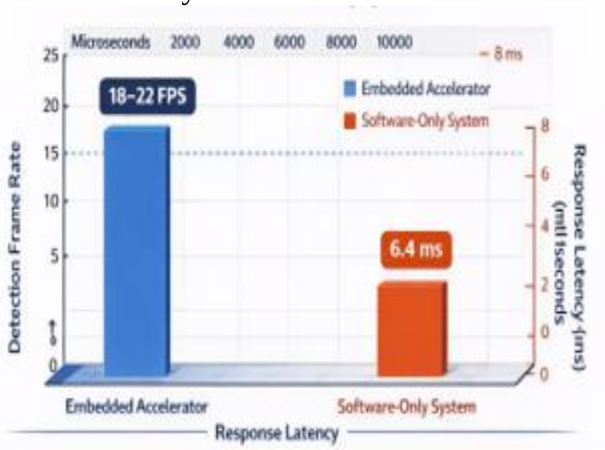

Figure 2 Performance Comparison: Embedded Deep Learning Accelerator vs. Software-Only System

4.2. Discussion

The results demonstrate the effectiveness of combining deep learning with FPGA assistance for perimeter security. YOLO provides high detection accuracy, while FPGA ensures deterministic control. The architecture minimizes latency and improves reliability in real-time environments. Compared to traditional CCTV systems, the proposed design offers autonomous operation, faster response, and improved scalability. However, performance depends on lighting conditions and camera quality. Future improvements can integrate thermal imaging and FPGA-based neural acceleration for higher throughput.

Conclusion

This paper presented the development of an embedded deep learning accelerator for real time perimeter security using Raspberry Pi and FPGA assistance. The integration of YOLO based vision intelligence with SLG47910 FPGA control provides low latency, reliable, and automated surveillance. The proposed system enhances security response, reduces human dependency, and supports scalable deployment in defense and industrial environments. Future work will focus on multi-sensor fusion and direct FPGA acceleration of neural networks.

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