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AI-Driven Smart Micro Radar Security System for Intelligent Intrusion Detection

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***Abstract*—Conventional surveillance systems rely on continuous monitoring, resulting in excessive energy consumption, redundant data storage, and high false alarm rates. This paper presents an AI-driven smart micro radar security system that operates using an event-based detection approach to overcome these limitations.**

The proposed system integrates an ultrasonic sensing mechanism with an embedded microcontroller to detect physical intrusion within a predefined range. Upon detection, an ESP32- CAM module is activated from a low-power state to capture an image. The captured image is processed using a hybrid computer vision pipeline combining deep learning-based object detection and classical face detection techniques.

A confidence-based decision mechanism is implemented to classify detected entities as human or non-human, significantly reducing false positives. Experimental results demonstrate low latency, efficient power utilization, and reliable performance under real-time conditions. The system offers a cost-effective and scalable solution for intelligent surveillance applications.

***Index Terms*—Intrusion Detection, Smart Surveillance, Ultra- sonic Sensor, ESP32-CAM, YOLOv8, Edge AI**

I. Introduction

The rapid growth of smart surveillance technologies has increased the demand for efficient, intelligent, and resource- aware monitoring systems. Conventional surveillance systems primarily rely on continuous video recording [1], which results in excessive power consumption, redundant data storage, and frequent false alarms triggered by non-human activities such as pets, moving objects, or environmental disturbances. These limitations not only reduce system efficiency but also increase the burden on storage and human monitoring.

To overcome these challenges, this work proposes an event- driven smart micro radar security system that operates on a selective activation principle. Instead of continuously monitoring the environment remains in a low-power state and becomes active only when a potential intrusion is detected. This significantly reduces unnecessary resource usage while maintaining real-time responsiveness.

The proposed system integrates low-cost embedded hard- ware with intelligent image-based verification to improve detection accuracy. An ultrasonic sensor mounted on a servo motor performs continuous scanning of the surrounding area to detect nearby objects based on distance measurements. Once an object is detected within a predefined threshold, the system triggers a camera module to capture an image for further analysis.

The primary contribution of this work is the implementation of a dual-stage detection mechanism that combines physical sensing with artificial intelligence. In the first stage, ultrasonic sensing enables efficient and low-cost proximity detection without continuous data generation. In the second stage, computer vision techniques [2] are employed to verify whether the detected object corresponds to a human presence. This verification step plays a crucial role in reducing false positives and improving overall system reliability.

In addition to improving detection accuracy, the proposed approach emphasizes energy efficiency by incorporating event- driven activation and low-power hardware operation. The inte- gration of embedded systems with AI-based decision-making makes the system suitable for practical deployment in real-world scenarios such as home security, smart surveillance, and IoT-based monitoring environments.

Overall, this work demonstrates how combining simple sensing mechanisms with intelligent processing can lead to a more reliable, efficient, and scalable security solution compared to traditional surveillance systems.

II. Related Work

Ultrasonic sensing has been extensively utilized in embedded and IoT-based systems for applications such as distance measurement, obstacle detection, and basic intrusion sensing [3].

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These systems are widely preferred due to their low cost, ease of integration, and minimal computational requirements. However, ultrasonic-based approaches are inherently limited in their ability to classify detected objects, as they rely solely on distance information without semantic understanding of the environment. As a result, they are prone to generating false alarms when triggered by non-human entities.

In parallel, computer vision techniques have undergone significant advancements with the emergence of deep learning [4]. Early approaches such as Haar Cascade classifiers [5] and Eigenfaces [6] laid the foundation for face and object detection with relatively low computational cost. However, modern deep learning-based models have significantly improved detec- tion accuracy and robustness. Convolutional Neural Networks (CNNs), popularized by works such as AlexNet [7] and further enhanced by architectures like ResNet [8], have enabled large- scale image understanding.

Region-based detectors such as Faster R-CNN [9] intro- duced improved accuracy through region proposal mechanisms but at the cost of higher computational complexity. In con- trast, real-time object detection models such as YOLO [2] and its recent variants [10] have demonstrated remarkable performance in detecting human presence with high speed and accuracy. These models perform detection and classification in a single forward pass, making them suitable for real- time surveillance applications. Lightweight architectures such as MobileNet [11] further enable deployment on resource- constrained edge devices.

To improve model generalization, data augmentation tech- niques [12] have been widely adopted in deep learning pipelines, enhancing robustness against variations in lighting, orientation, and occlusion.

Recent research has also explored RF-based sensing ap- proaches for human detection. These systems can detect movement even through obstacles [13], offering robustness under challenging environmental conditions. However, they often lack fine-grained classification capabilities compared to vision-based systems.

Several intelligent surveillance systems have been proposed that leverage computer vision for automated monitoring. Al- though these systems provide improved recognition capa- bilities, they typically rely on continuous video processing, leading to high power consumption and computational over- head. Additionally, their performance degrades in low-light or occluded environments [14].

With the rise of IoT and edge computing, there has been a growing interest in deploying AI models closer to the data source [1]. Edge-based architectures reduce latency, bandwidth usage, and dependency on cloud infrastructure.

Furthermore, fog computing paradigms [15] support distributed processing for scalable real-world applications such as smart home secu- rity [16].

Despite these advancements, most existing systems treat sensing and intelligence as separate components. Sensor-based systems lack contextual understanding, while vision-based systems suffer from inefficiency due to continuous processing. The proposed system addresses these limitations by integrat- ing ultrasonic sensing with AI-driven visual verification in an event-driven framework. This hybrid approach combines the efficiency of hardware-based detection with the intelligence of deep learning models, resulting in improved accuracy, reduced false alarms, and optimized resource utilization.

III. System Architecture

The proposed system is designed as a hybrid architecture that combines low-power edge sensing with intelligent pro- cessing. It is organized into two primary layers to optimize performance, energy efficiency, and detection accuracy.

A. Edge Sensing Layer

The edge sensing layer is responsible for continuous envi- ronmental monitoring using lightweight and energy-efficient components. An HC-SR04 ultrasonic sensor is mounted on a servo motor, enabling angular scanning across a defined range (typically 0°–180°). This scanning mechanism mimics a radar- like behavior, allowing the system to monitor a wider area with a single sensor.

The ultrasonic sensor operates based on the time-of-flight principle, where the time taken for an emitted sound wave to reflect back from an object is used to calculate distance. This enables real-time proximity detection with minimal computa- tional overhead.

When an object is detected within a predefined threshold distance (e.g., 30 cm), the microcontroller (Arduino) immedi- ately initiates an event-driven response. A buzzer is activated to provide an instant alert, and a trigger signal is sent to wake the ESP32-CAM module from its deep sleep state. This design ensures that high-power components such as the camera and Wi-Fi module remain inactive during idle conditions, significantly reducing overall power consumption.

B. Processing Layer

The processing layer is responsible for intelligent analysis and decision-making. Once activated, the ESP32-CAM cap- tures an image of the detected scene and transmits it to a local processing unit over a Wi-Fi connection.

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The received image undergoes preprocessing steps such as resizing and enhancement to improve detection quality. A hybrid artificial intelligence framework is then applied to analyze the image.

A lightweight deep learning model, YOLOv8 Nano, is used to detect human body features due to its balance between accu- racy and computational efficiency. In parallel, a Haar Cascade classifier is employed to detect facial regions, providing an additional layer of verification.

The outputs from both detection models are combined to compute a Human Confidence Score, which quantifies the likelihood of the detected object being a human. This dual-verification mechanism enhances robustness by reducing false positives caused by non-human objects or environmental disturbances.

Overall, the layered architecture enables efficient coor- dination between hardware-level sensing and software-level intelligence, resulting in a reliable, low-power, and scalable intrusion detection system.

IV. Methodology

The proposed system follows a structured, event-driven workflow that integrates hardware-based sensing with AI-driven verification. The complete process is designed to ensure efficient operation, reduced power consumption, and accurate intrusion detection.

Initially, the ultrasonic sensor mounted on a servo motor continuously scans the surrounding environment over a prede- fined angular range. This scanning mechanism enables real- time monitoring of object presence by measuring distance using the time-of-flight principle.

When an object is detected within a predefined threshold distance, the system transitions from idle mode to active mode. The microcontroller immediately triggers a buzzer to indicate a potential intrusion and simultaneously activates the ESP32- CAM module from its low-power sleep state.

Once activated, the ESP32-CAM captures an image of the detected scene and transmits it to a local processing unit via a wireless connection. The received image undergoes preprocessing, which may include resizing, noise reduction, and contrast enhancement to improve detection accuracy.

The processed image is then analyzed using a hybrid artifi- cial intelligence pipeline. A YOLOv8 Nano model is applied to detect human body features due to its capability for fast and accurate object detection. In parallel, a Haar Cascade classifier is used to detect facial regions, providing an additional layer of verification.

Based on the outputs from both models, a Human Confi- dence Score is computed. This score represents the likelihood that the detected object is a human.

A predefined threshold is used to classify the result into two categories: human detected or non-human (false alarm).

This dual-stage methodology ensures that the system not only detects the presence of objects but also intelligently ver- ifies their nature, thereby significantly reducing false positives while maintaining real-time performance.

V. Results And Discussion

The proposed system was experimentally evaluated under controlled indoor conditions to analyze its performance in terms of response time, detection accuracy, false positive reduction, and power efficiency.

The hardware response time, defined as the delay between object detection and system activation, was observed to be less than one second. This includes ultrasonic sensing, microcon- troller processing, and activation of the ESP32-CAM module. The AI-based image classification process was completed within a few seconds on a standard computing platform, enabling near real-time operation.

The hybrid detection approach demonstrated a significant improvement in reducing false positives. During testing, non- human objects such as moving hands, static obstacles, and environmental disturbances were correctly classified as non- threats. In contrast, human subjects consistently produced higher confidence scores and were accurately identified as valid intrusions. This validates the effectiveness of combining ultrasonic sensing with AI-based verification.

In addition to detection accuracy, the system showed notable improvements in energy efficiency. The ESP32-CAM module remained in deep sleep mode during idle conditions and was activated only when necessary. This event-driven operation re- duced unnecessary power consumption compared to traditional surveillance systems that rely on continuous video streaming. Overall, the results indicate that the proposed system achieves a balanced trade-off between performance and re- source utilization. The integration of hardware-based sensing with intelligent processing enhances system reliability, making it suitable for practical deployment in real-world security applications.

VI. Advantages

- *Energy-Efficient Operation:* The event-driven architec- ture ensures that high-power components such as the camera and Wi-Fi module remain inactive during idle conditions, significantly reducing overall power consump- tion.

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- *Reduced False Positives:* The integration of ultrasonic sensing with AI-based verification enables accurate dif- ferentiation between human and non-human objects, min- imizing false alarms caused by environmental distur- bances.
- *Cost-Effective Implementation:* The system is built using low-cost and widely available components such as Arduino, HC-SR04, and ESP32-CAM, making it acces- sible for practical deployment.
- *Real-Time Detection:* The combination of fast hardware sensing and lightweight AI models enables near real-time intrusion detection without requiring high-end computa- tional resources.
- *Scalable and Modular Design:* The architecture allows easy integration of additional sensors, advanced AI mod- els, or communication modules, making it adaptable for various applications.
- *Low Data Redundancy:* Unlike traditional systems that continuously record video, the proposed system captures data only during events, reducing unnecessary storage usage.

VII. Limitations

- *Limited Detection Range:* The ultrasonic sensor oper- ates within a constrained range (typically up to a few meters), which restricts the effective coverage area in large-scale environments.
- *Environmental Sensitivity:* The performance of the ultrasonic sensor may be influenced by environmental factors such as ambient noise, temperature variations, and surface characteristics, potentially affecting measurement accuracy.
- *Dependence on External Processing:* The AI-based classification is performed on an external processing unit, making the system dependent on network connectivity and processing availability for real-time decision-making.
- *Latency in Image Processing:* Although the system operates in near real-time, image transmission and AI inference introduce a slight delay compared to purely hardware-based detection systems.
- *Limited Field of View:* The narrow beam angle of the ultrasonic sensor necessitates mechanical scanning using a servo motor, which may reduce overall scanning speed and responsiveness.

VIII. Future Work

The proposed system can be further enhanced in several directions to improve performance, scalability, and real-world applicability.

One potential improvement is the integration of advanced sensing technologies such as LIDAR or mmWave radar mod- ules, which can provide higher accuracy, longer detection range, and better performance under varying environmental conditions.

Another important extension involves deploying edge AI models directly on embedded hardware such as ESP32 or dedicated AI-enabled microcontrollers. This would eliminate the dependency on external processing units, reduce latency, and enable fully autonomous operation.

The system can also be extended by incorporating wireless communication and mobile-based alert mechanisms. Real-time notifications through a mobile application or cloud-based plat- form would enhance usability and enable remote monitoring of the surveillance system.

Additionally, replacing the servo-based scanning mechanism with a stepper motor or implementing multi-sensor arrays can improve coverage area and scanning precision. This would allow the system to monitor larger environments more effi- ciently.

Further enhancements may include the integration of data logging, anomaly detection, and adaptive threshold mecha- nisms using machine learning techniques, enabling the system to learn from environmental patterns and improve decision- making over time.

Overall, these improvements can transform the proposed system into a more robust, intelligent, and fully autonomous smart surveillance solution suitable for large-scale deployment.

IX. Conclusion

This paper presented an AI-driven smart micro radar se- curity system that integrates embedded sensing with intel- ligent image-based verification to address the limitations of traditional surveillance systems. By adopting an event-driven approach, the system significantly reduces unnecessary power consumption and data redundancy associated with continuous monitoring.

The implementation of a dual-stage detection mechanism, combining ultrasonic sensing with AI-based human verifica- tion, enhances detection accuracy while effectively minimizing false alarms.

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Experimental results demonstrate that the system is capable of near real-time operation with reliable performance under controlled conditions.

In addition to its technical effectiveness, the proposed so- lution offers a cost-efficient and scalable architecture, making it suitable for deployment in practical applications such as home security, smart surveillance, and IoT-enabled monitoring systems.

Furthermore, the system can be extended in the future by incorporating advanced edge AI models and multi-sensor fusion to enhance adaptability and performance in diverse real- world environments.

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