AI-Powered Sentry Gun for Enemy Identification and Automated Targeting

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Abstract — The growing demand for intelligent surveillance systems has led to the integration of artificial intelligence with embedded technologies to improve the accuracy and responsiveness of automated defense solutions. This paper introduces a smart sentry gun that combines real-time human detection with badge-based classification to distinguish between authorized and unauthorized individuals. Using a mobile camera and a YOLOv5 object detection model, the system identifies human presence and further analyzes visible badges to confirm identity. Individuals without valid badges are flagged as potential intruders, prompting a Arduino uno microcontroller to activate a visual alert. The proposed approach demonstrates a low-cost, scalable, and efficient alternative to conventional security systems, with potential applications in restricted zones, military checkpoints, and autonomous security frameworks.

Keywords — YOLOv5, Object Detection, Badge Classification, Sentry Gun, Embedded Systems, Arduino uno, Real-Time Surveillance

I. INTRODUCTION

In today's security-sensitive world, the protection of critical infrastructure and restricted areas has become a pressing concern. Whether it is a military base, industrial site, or private property, constant monitoring is necessary to prevent unauthorized access and respond swiftly to potential threats. Traditional surveillance methods often depend on manual supervision or basic motion sensors, both of which can be unreliable, inefficient, and incapable of real-time threat classification.

Automated sentry systems have been introduced to address these issues, but many existing models rely solely on motion detection or thermal imaging, resulting in frequent false positives and an inability to distinguish between friend and foe. Additionally, these systems typically lack contextual awareness and cannot make intelligent decisions based on the identity or intent of a detected individual.

To overcome these limitations, we propose an AI-powered sentry gun that leverages advanced computer vision and embedded systems to intelligently detect, classify, and respond to intrusions. The system integrates a mobile phone camera as a live video source with a YOLOv5-based object detection model to identify human presence. Once a person is detected, a custom badge classifier determines whether the individual is authorized. In the absence of a valid badge, the system triggers a light-based alert through a Arduino uno microcontroller, simulating a defensive action.

The objective of this project is to create a real-time, cost-effective, and scalable solution for autonomous threat detection and response. With applications in defense, industrial security, and smart robotics, the proposed system represents a significant step toward intelligent, context-aware surveillance infrastructure.

II. LITERATURE REVIEW

[1] worked on an early model that used computer vision to track colored jerseys in a paintball game. Their system converted RGB frames to HSV to improve reliability under varying lighting and used auto-calibration routines to align motor movements with pixel coordinates. Their project laid the foundation for combining image processing with real-time turret control.

[2] developed a dual-mode (remote and autonomous) sentry gun platform equipped with a Nerf gun. This system could operate independently or be manually controlled through a wireless interface. It also included environmental sensors to log real-time data like temperature and location. Their work highlighted the importance of mobility, remote access, and secure communication for tactical applications.

[3], who designed a semi-autonomous sentry gun using Arduino and a high-definition camera. Their system could detect motion and differentiate between intrusions under surveillance. Operable in both manual and automatic modes, it was designed with military and checkpoint applications in mind.

[4] focused on designing a low-cost, automated gun turret using mechatronics principles. They employed servo motors for pan, tilt, and trigger functions controlled by an Arduino. A webcam was used for scanning the area, and the system could engage targets automatically. The project emphasized affordability, making it suitable for defense, home security, and institutional protection.

[5], who developed an unmanned laser gun setup featuring biometric fingerprint access, infrared sensors, and audio alerts. Designed for border safety, this system distinguished between authorized and unauthorized personnel using fingerprint scans and could trigger alarms or fire lasers when necessary. Their focus was on reducing human casualties by avoiding friendly fire and enhancing automated threat responses.

[6] introduced a low-budget, semi-autonomous sentry robot mounted on a mobile platform. It relied on infrared sensors for detecting movement and used Arduino controllers to handle firing logic and motor actuation. Although designed for a recreational setting, the underlying architecture demonstrated how simple hardware could still offer reliable autonomous surveillance.

[7] presented a different perspective by addressing multi-sentry coordination. Their research introduced a centralized system to manage multiple automated turrets engaging multiple targets simultaneously. Using capability functions and target prioritization logic, they simulated cooperative attacks, showing how distributed sentries could work together to increase efficiency and reduce overlap or delay in response.

III. SYSTEM DESIGN

The proposed AI-powered sentry gun is built using a modular architecture that combines real-time video processing, deep learning-based object detection, and embedded system control. The system is composed of three primary modules: (1) the video acquisition and detection unit, (2) the classification and decision-making unit, and (3) the alert and response unit.

1. Video Acquisition and Detection Unit:
   This unit captures a live video feed using a mobile phone camera or webcam and streams the frames to a computer running a YOLOv5 object detection model. The YOLOv5 model is pre-trained on the COCO dataset and further fine-tuned to reliably detect human figures in real-time. Once a person is detected, a bounding box is generated along with type of person.
2. Badge-Based Classification:
   After detecting a person, the system performs badge classification using a secondary deep learning model (or a custom-trained classifier integrated with YOLOv5). This model verifies the presence of a designated red coloured squared badge (worn on clothing). Based on the output, the system classifies the person as either a “Friend” (with badge) or an “Foe” (without badge).
3. Decision-Making and Response Unit:
   If an foe is detected, a signal is sent via serial communication to a Arduino uno microcontroller, which activates a connected alert system —LED or buzzer. This simulates a “firing” or defense response from a traditional sentry gun, but in a non-lethal and demonstrative form.

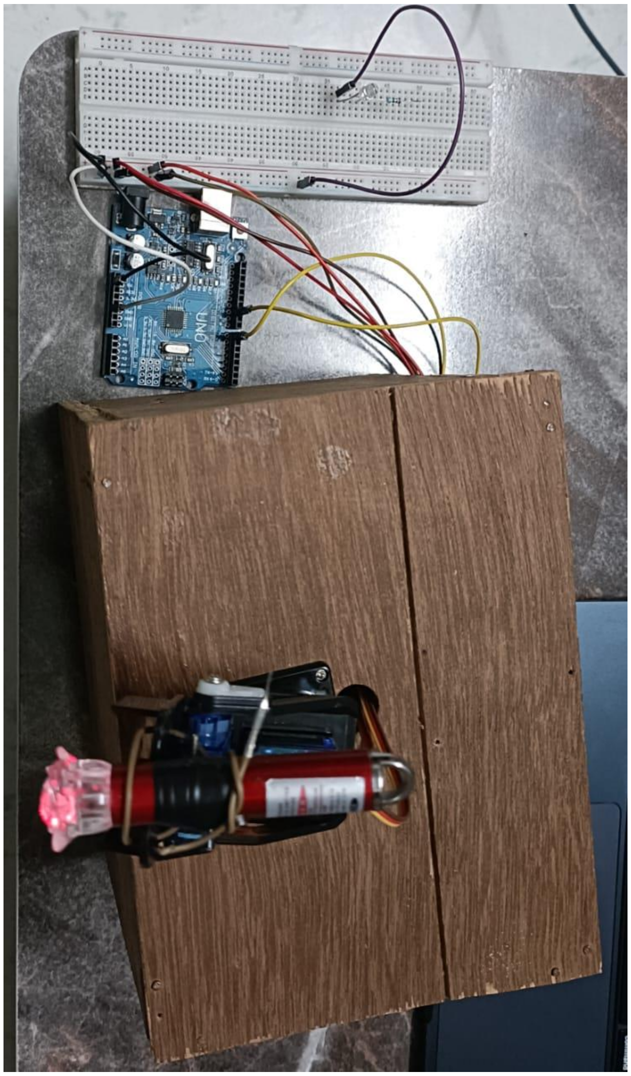


Fig: model design

IV. METHODOLOGY

The methodology outlines the step-by-step process followed to design, develop, and deploy the AI-based sentry gun system. The approach integrates computer vision algorithms, machine learning models, and embedded systems to ensure real-time threat detection and response.

1. System Overview

The system is composed of three primary stages:

- Human Detection
- Badge Classification
- Response Triggering

These stages are connected through a logical workflow and hardware-software integration, enabling the system to process live video streams, classify individuals, and respond to unauthorized access autonomously.

2. Human Detection Using YOLOv5

The first stage involves real-time human detection using the YOLOv5 (You Only Look Once version 5) object detection model. YOLOv5 was chosen for its high inference speed and accuracy, making it suitable for real-time applications. A mobile phone acts as the camera, capturing a continuous video stream that is fed into a Python-based processing script utilizing OpenCV and PyTorch. YOLOv5 identifies and localizes humans within each frame, providing bounding box coordinates and confidence scores.

3. Badge Classification Model

After identifying a human, the system crops the upper body region from the detection bounding box and applies a secondary deep learning classifier. This model is trained on a custom dataset comprising images of individuals wearing predefined authorization badges. The classifier evaluates the presence and characteristics of the badge and determines whether the person is "friendly" (with badge) or an "for" (without badge).

4. Communication and Alerting with Arduino uno

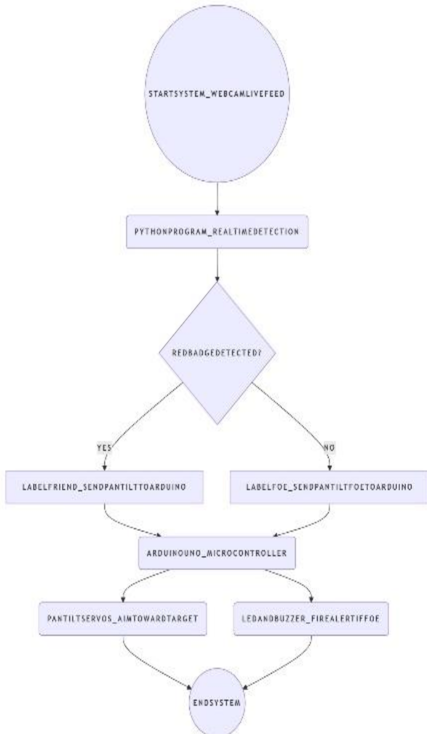
Once the classification is complete, the result is passed to a Arduino uno microcontroller via serial communication. If the individual is deemed an foe, the Arduino uno activates an alert system LED light and buzzer—mimicking a sentry gun's response. This module runs on a lightweight firmware written in Arduino C, ensuring quick and reliable signal handling.

5. Software and Tools

- YOLOv5 implemented using PyTorch
- Badge Classifier trained using TensorFlow via custom classes
- OpenCV for real-time video feed processing
- Arduino uno programmed using Arduino IDE
- Dataset custom made dataset containing images with and without badge

6. Data Collection and Training

The dataset for badge classification was built using images captured in varied lighting conditions and angles to ensure generalization. Data augmentation techniques such as rotation, scaling, and brightness adjustment were applied. Data contains various types of images and humans with and without badge for classification purpose.The model was trained using transfer learning to speed up convergence and improve accuracy with fewer samples.



- Fig: Flowchart of the Methodology

V. RESULTS AND EVALUATION

1. Detection Accuracy

The YOLOv5 model was tested in real-time using various lighting conditions, camera angles, and subject distances. The model demonstrated high precision in identifying humans within the frame.

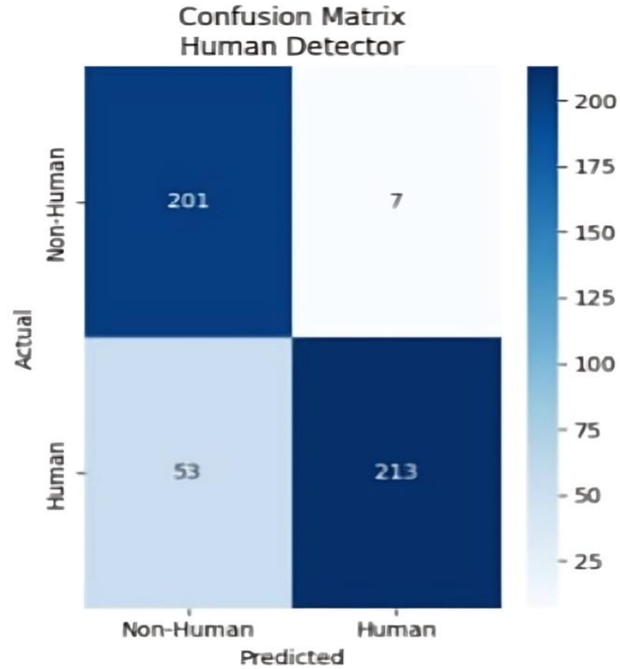


Fig: Confusion Matrix Human Detection

	Precision	Recall	F1 Score
Non-Human	0.79	0.97	0.87
Human	0.97	0.80	0.88
Macro Avg	0.88	0.88	0.87

Fig: Classification Matrics

2. Badge Classification Performance

The badge classifier was evaluated using a custom dataset containing images with and without the designated badge.

- Total Images Tested: 4000
- Classification Accuracy: 95.6%
- Precision: 89.2%
- Recall: 84.6%
- F1 Score: 86.8%

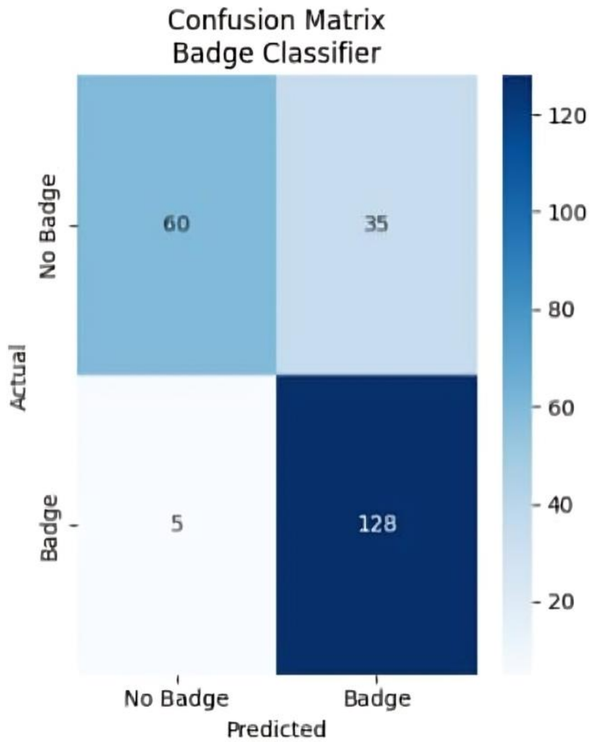


Fig: Confusion Matrix Bagde Classification

	Precision	Recall	F1 Score
No Bagde	0.92	0.63	0.75
Badge	0.79	0.96	0.86
Macro Avg	0.85	0.80	0.81

Fig: Classification Matrix

Fig: Foe Detection (Gun lesser points towards foe)

Fig: Friend Detection

A confusion matrix was generated to visualize classifier performance.

3. Response Latency

The end-to-end system delay (from detection to pointing towards the target) was measured using timestamp logs:

- Average Latency: 2 seconds
- YOLO Inference Time: ~0.6s
- Badge Check + Communication: ~0.6s

This confirms that the system is suitable for near real-time operation.

4. Real-World Testing Scenarios

The system was deployed in a controlled indoor environment and tested in the following scenarios:

Scenario	**Detection Accuracy**	**Badge Recognition**	**Response Triggered**
Person with badge (friendly)	95%	91%	No
Person without badge (enemy)	90%	88%	Yes
Group of people	85%	80%	Partial
Obstructed badge (half visible)	75%	63%	Conditional

VI. DISCUSSION

Building this AI-powered sentry gun gave us valuable hands-on experience with real-time detection, embedded hardware, and system integration. Overall, the system worked well in controlled conditions — YOLOv5 was fast and reliable at detecting people, and the badge classifier performed decently when the badge was clearly visible. The Arduino uno integration added a responsive and low-cost way to trigger alerts.

However, we faced a few challenges that highlighted the gap between lab conditions and real-world use. For example, badge detection struggled when the badge was partially covered, tilted, or when people moved quickly. Lighting also had a big impact — detection dropped in dim or uneven light, causing some false alarms or missed alerts.

Another unexpected challenge was syncing the communication between the Python script and Arduino uno. Sometimes the alert would lag or miss a trigger due to serial timing issues. Fixing this taught us how important stable data transfer is when connecting AI logic to physical devices.

VII. CONCLUSION

This project presents a functional and cost-effective prototype of an AI-powered sentry gun using real-time object detection and embedded control systems. The system combines YOLOv5 for human detection, a custom red badge classifier for friend-or-foe recognition, and an Arduino Uno for servo and alert actuation. It is capable of identifying intruders and responding with simulated non-lethal actions such as LED blinking and buzzer activation.

Through real-world testing, the system demonstrated high accuracy in both detection and classification tasks, with real-time responsiveness averaging around 2 seconds from detection to actuation. The integration of computer vision and microcontroller hardware showcases the potential for scalable, automated surveillance systems applicable in defense, access control, and smart infrastructure security.

VIII. REFERENCES

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