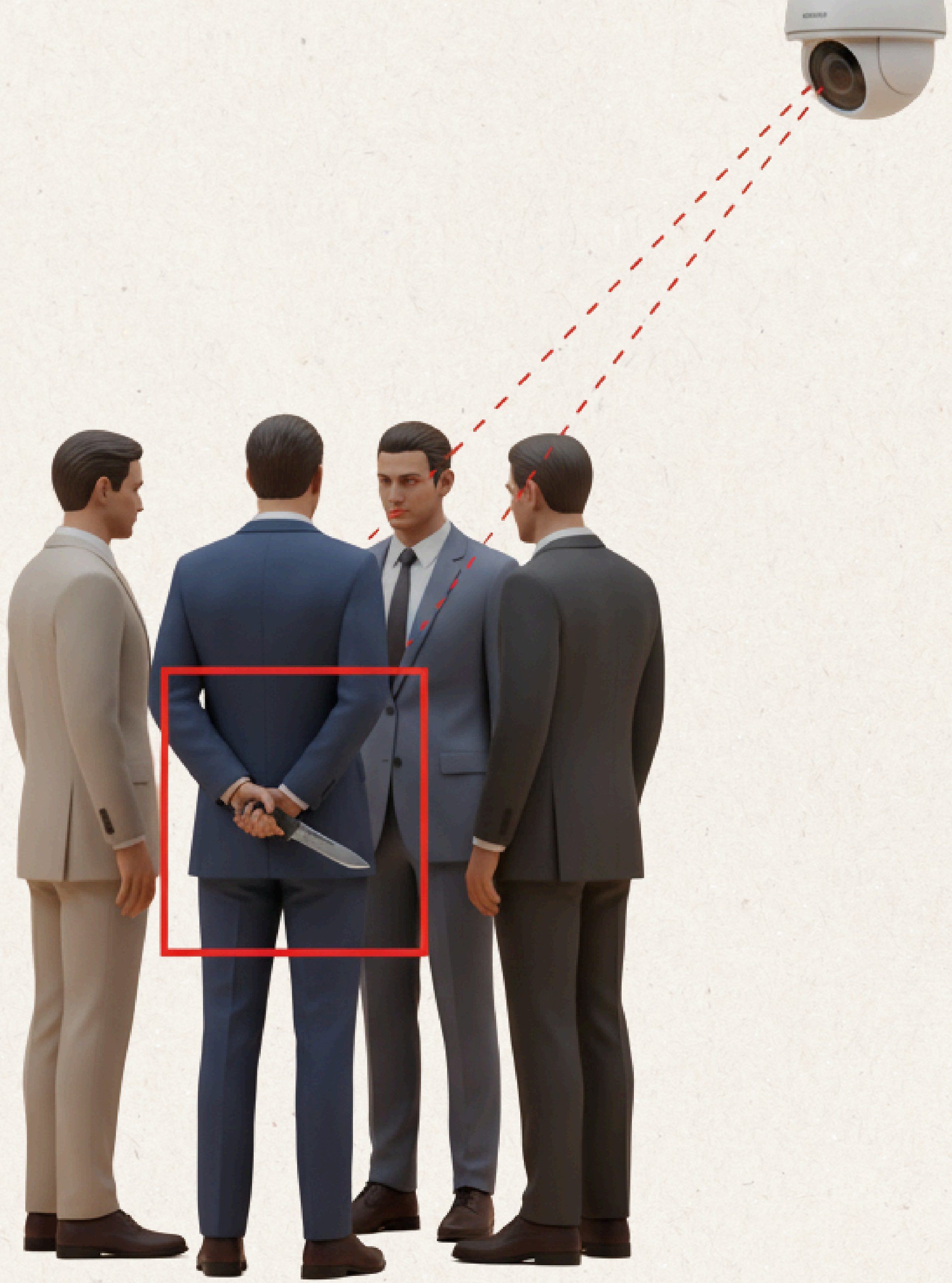
DEEP LEARNING-POWERED SMALL OBJECT DETECTION FOR SMART SURVEILLANCE



A Focus on Gun and Knife Identification

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Agenda

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INTRODUCTION

Gun and knife-related crimes have become a serious concern in many countries, threatening public safety in schools, airports, and other vulnerable places. Studies show that even the simple access to a weapon can significantly increase the probability of violent behavior.

CCTV systems are widely used for security, but manual monitoring is inefficient. Human operators often experience "video blindness" after 20–40 minutes, missing up to 95% of activity and reducing detection accuracy, making manual surveillance unreliable for timely threat response.

With advancements in computer vision and deep learning, researchers are now focusing on developing automatic weapon detection systems. Unlike general object detection, gun and knife detection is far more challenging due to their small size, possible concealment, and similarity with everyday objects. Despite its importance, very few successful systems have been implemented in real-world surveillance.

Literature Review

REVIEW LINK

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PROBLEM STATEMENT

Title :

Deep Learning-Powered Small Object Detection for Smart Surveillance: A Focus on Gun and Knife Identification

Description :

This project aims to develop a smart surveillance system capable of real-time detection of small threat objects such as guns and knives using deep learning based computer vision techniques. By leveraging advanced convolutional neural networks CNNs the system accurately identifies weapons in complex environments, enhancing public safety and enabling proactive threat response in sensitive areas like schools, airports, and public gatherings

Objectives and Goals

Goal 1

To develop a deep learning-powered smart surveillance system capable of real-time detection of small threat objects such as guns and knives.

Goal 2

To enhance public safety by reducing reliance on human operators and enabling faster, accurate threat identification.

Goal 3

To address challenges like small object size, concealment, and similarity with everyday objects, improving detection performance in complex environments.

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Existing System Analysis

Several approaches exist for weapon detection. Pre-trained models like **YOLOv8** offer fast and accurate real-time detection using annotated datasets. Methods such as **IMGF with ROI** extraction leverage template generation and background subtraction to detect moving weapons. **Background segmentation** approaches (PBAS, ViBE, ISBM, GMM) handle challenging outdoor conditions with varying lighting and weather. **Template matching** techniques use edge-based templates for guns and knives but face high time complexity. Advanced deep learning models like **GSNet** enhance small object detection through **DenseNet** and **SAN** blocks. Finally, **ROI with holistic** classification extracts localized gun features in video frames, improving accuracy in complex environments. Each method contributes uniquely, but deep learning–based models (like YOLOv8, GSNet) show superior performance for real-time surveillance.

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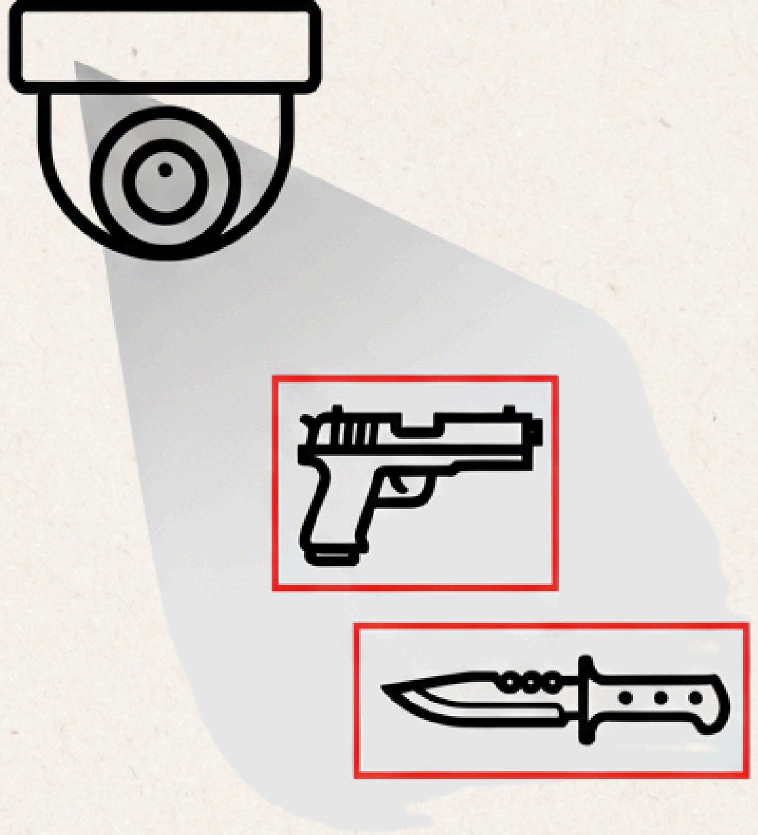
Draw Backs



Models like YOLOv8 produce false-positives if not annotated and trained properly, and computational costs are high for real-time deployment

Models based on template matching algorithms cannot detect weapons that are partially occluded by an object.

Models based on ROI and Holistic-based classification using older algorithms like VGG16 struggle to identify small or partially occluded guns.

Models like GSNet suffer from large intra-class variability, strong backgrounds, increased memory usage and occluded/noisy backgrounds.

Apart from model performances, challenges like improper dataset handling and preparation, environmental situations like illuminations, motion-blur and occlusions, data augmentation challenges like rotation and scaling of images during training and testing also affect greatly in detecting weapons in real-world scenarios

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DATA SET

Total Images (approx.): 4,50,000+ (from multiple public datasets)

Categories:

Positive (+ve): Weapon images (guns, knives).

Negative (–ve): Non-weapon images (background, people without weapons, random objects).

Data Sources:

IMFDB (Internet Movie Firearm Database): ~4,50,000 firearm images.

Knives Image Database: 12,899 images → 3,559 positive (knives), 9,340 negative (non-weapons).

Olmos et al. Dataset: 9,261 pistol images, 19,381 knife images.

ITU Firearm Dataset: 10,973 firearm images with 13,647 weapon instances.

Gun Movies Dataset: 7 CCTV-style videos (~24,000 frames).

Data Split (planned):

Training Set (80%) – for model training.

Testing Set (20%) – for performance evaluation.

Dataset Structure:

Separate folders for Gun (+ve), Knife (+ve), Non-Weapon (–ve) in both Training & Testing.

Bounding box annotations created in Roboflow for YOLOv8 training.

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Conclusion

- We identified the problem of small object detection for smart surveillance, focusing on guns and knives.
- Conducted a literature review and analyzed existing systems (YOLOv8, IMGF, background segmentation, template matching, GSNet, ROI-based methods).
- Highlighted the representation methods used (bounding boxes, templates, ROI, background-foreground separation, feature maps).
- Understood the challenges faced by existing models, such as false positives, occlusion issues, noisy backgrounds, dataset preparation, and environmental factors.
- Prepared resources for the next phase: dataset collection & annotation in Roboflow, and implementation using YOLOv11.

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