International Journal of Computational Research in Science and Technology
E-ISSN: 3108-0871, Volume 2 Issue 5
Sep-Oct-2026, PP 01-05

Weapon Detection Using Artificial Intelligence: A Review Of Deep Object Detection In Cctv Video And X-Ray Security Screening

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Abstract—Public places such as railway stations, airports, schools, malls and religious gatherings need to detect weapons quickly to prevent violent incidents. Human operators monitoring many camera feeds or reading X-ray baggage images can miss threats because of fatigue and the rarity of real events. This paper reviews AI-based weapon detection in two settings: visible-light CCTV video, where handguns, rifles and knives must be detected in real time, and X-ray security screening, where prohibited items must be recognized in cluttered, overlapping baggage images. It examines deep object detectors, including two-stage region-based networks, single-stage YOLO-family detectors, feature pyramid networks and focal loss for small and rare objects, and surveys specialized datasets and studies for handgun detection in video and threat detection in X-ray imagery. Practical issues such as small object size, occlusion, similar-looking objects, low-light video and false alarms are analysed. A five-layer architecture comprising video and X-ray input, preprocessing, a detection engine, alert verification by human operators and a response layer is proposed, with research gaps, objectives, a comparison of detectors and challenges including privacy and bias. The review concludes that AI can strengthen security when it acts as an alert system supervised by trained personnel.

Index Terms—Weapon detection, object detection, YOLO, Faster R-CNN, CCTV surveillance, X-ray baggage screening, public safety, deep learning

I. Introduction

Security staff in a control room may watch dozens of camera feeds at once, and baggage screeners inspect thousands of X-ray images each shift. Weapons appear rarely, are often small or partly hidden, and must be noticed within seconds. Fatigue and the low base rate of threats make human-only monitoring unreliable.

Deep learning object detectors can scan every frame and image continuously and raise an alert when a weapon is likely present. Olmos *et al.* [1] showed that a deep detector could recognize handguns in videos and trigger an alarm, and Akcay *et al.* [2] applied deep CNNs to detect threats in X-ray baggage images.

This paper reviews AI-based weapon detection in CCTV and X-ray screening and proposes an architecture that keeps humans in control of responses.

II. Theoretical Background

2.1 Detection Settings

Fig. 1 summarizes the two settings and their object classes: firearms and knives in visible-light video, and guns, knives, explosives components and other prohibited items in X-ray images.

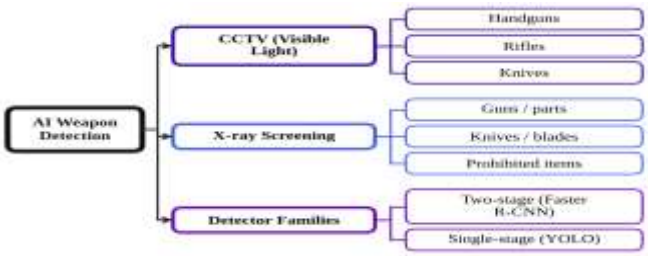


Fig. 1. Weapon detection settings and target classes.

2.2 Object Detection Basics

Two-stage detectors such as Faster R-CNN [3] propose regions and classify them, single-stage detectors such as YOLO [4], [5] predict boxes in one pass for real-time speed, feature pyramid networks [6] help detect small objects, and focal loss [7] addresses the imbalance between rare objects and background.

III. Survey of Existing Approaches

Grega *et al.* [8] developed early methods for detecting firearms and knives in CCTV images and highlighted the difficulty of reducing false alarms in real surveillance footage. Olmos *et al.* [1] trained a Faster R-CNN-based detector on a purpose-built handgun dataset and showed reliable alarms in video, improving results by carefully selecting training images.

González *et al.* [9] argued that real-time gun detection in CCTV remains an open problem because of small object size, motion blur and low resolution, and proposed synthetic data to augment scarce real footage. Bhatti *et al.* [10] compared modern detectors for weapon detection in real-time CCTV video and reported that YOLO-family models achieved a strong balance of precision and speed.

For X-ray screening, Mery *et al.* [11] released the GDXray database, and Akcay *et al.* [2] showed that transfer-learned CNNs outperform hand-crafted features for classifying and detecting threats in baggage. Miao *et al.* [12] introduced SIXray, a large dataset of real X-ray images with overlapping prohibited items, and a method to handle clutter and class imbalance. Table I summarizes these works.

Ref.	Author(s) / Year	Technique / Approach	Key Contribution	Limitation / Gap
[8]	Grega et al., 2016	Firearm and knife detection in CCTV	Early automated CCTV detection	False alarms
[1]	Olmos et al., 2018	Faster R-CNN handgun alarm	Reliable video alarms	Staged dataset
[9]	González et al., 2020	Real-time gun detection analysis	Synthetic data for scarce footage	Open problem remains
[10]	Bhatti et al., 2021	Comparison of detectors for CCTV	YOLO best speed–accuracy	Limited scenarios
[11]	Mery et al., 2015	GDXray database	Public X-ray images	Laboratory images
[2]	Akcay et al., 2018	Deep CNNs for X-ray baggage	Outperforms hand-crafted features	Limited threat classes
[12]	Miao et al., 2019	SIXray benchmark	Real overlapping X-ray items	Class imbalance
[7]	Lin et al., 2017	Focal loss (RetinaNet)	Handles rare objects	General detection

TABLE I Summary of Literature Survey

IV. Comparative Study

Table II compares detectors. Two-stage detectors are accurate but slower, single-stage YOLO models enable real-time video analysis and specialized X-ray models handle overlapping objects.

Detector	Accuracy	Speed	Best Setting
Faster R-CNN	High	Medium	Offline review, X-ray
RetinaNet (focal loss)	High	Medium	Rare small objects
YOLO family	High	Very fast	Live CCTV
FPN-based detectors	High (small objects)	Medium	Distant weapons

TABLE II Comparison of Detectors for Weapon Detection

V. Research Gaps

- Real weapon footage is scarce, so datasets are small or staged.
- Small, partially hidden weapons in low-resolution video are frequently missed.
- Harmless objects such as phones and tools cause false alarms.
- X-ray images vary across machines, and overlapping items confuse detectors.
- Privacy, bias and accountability for surveillance AI need clear policies.

VI. Aims and Objectives

- **O1:** To review deep object detection methods relevant to weapon detection.
- **O2:** To examine studies and datasets for CCTV and X-ray weapon detection.
- **O3:** To propose a human-supervised weapon detection architecture.
- **O4:** To compare detectors in accuracy and speed.
- **O5:** To identify challenges and future directions.

VII. Proposed Architecture

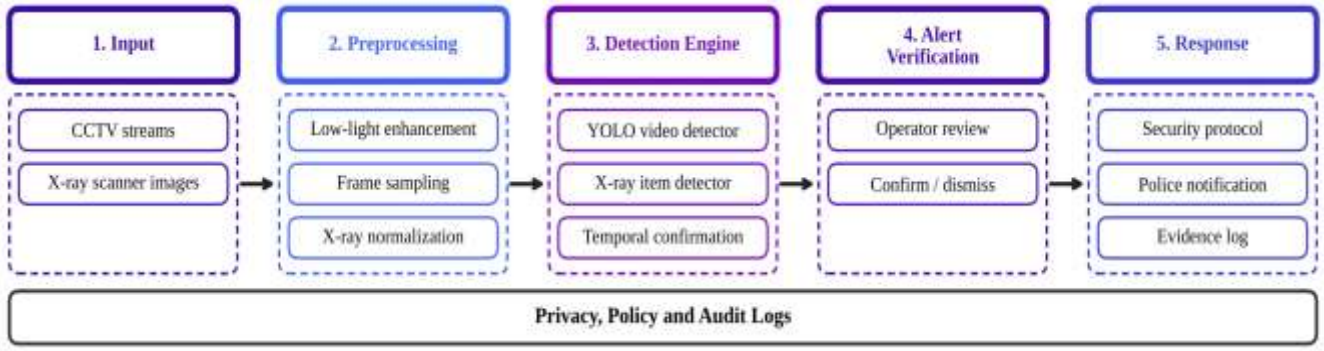


Fig. 2 shows the proposed architecture.

Fig. 2. Proposed human-supervised weapon detection architecture.

A. Input Layer

CCTV cameras stream video, and X-ray scanners provide baggage images, both to an edge server with a GPU.

7.2 Preprocessing Layer

Frames are resized, enhanced for low light and sampled; X-ray images are normalized and pseudo-coloured according to material type.

7.3 Detection Engine Layer

A YOLO-based detector identifies weapons in video, and a specialized detector trained on X-ray datasets identifies prohibited items. Temporal confirmation across several frames reduces false alarms.

7.4 Alert Verification Layer

Alerts with image crops and confidence are sent to trained operators, who confirm or dismiss them.

7.5 Response Layer

Confirmed alerts trigger security protocols, notify police or security teams and log evidence.

VIII. Process Flow and Evaluation

Fig. 3 describes the workflow. A detection is confirmed only if the weapon class appears with confidence above τ in at least k of the last n frames:

$$\Sigma_{i=t-n+1}^{t} \mathbb{1}[p_i > \tau] \geq k \qquad (1)$$

Detectors are evaluated with precision, recall and mean average precision at an IoU threshold, and with false alarms per hour for operational relevance.

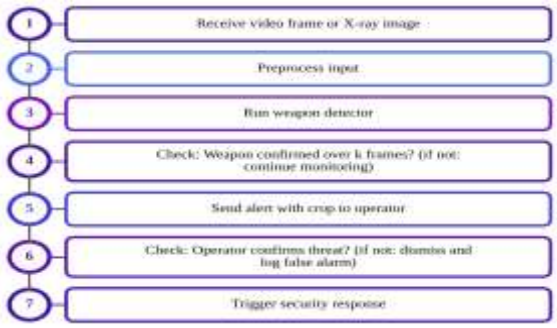


Fig. 3. Weapon detection and alert workflow.

IX. Limitations and Future Scope

Table III summarizes challenges. Future directions include synthetic data generation, multi-camera tracking of suspects, thermal and millimetre-wave imaging for concealed weapons and clear governance for surveillance AI.

TABLE III Challenges and Mitigation

Challenge	Mitigation
Scarce real data	Synthetic data; augmentation
Small, occluded weapons	High resolution; FPN; multi-frame
False alarms	Temporal confirmation; operator check
X-ray clutter	Overlap-aware models; dual-energy imaging
Privacy and bias	Clear policies; audits

X. Conclusion

AI-based weapon detection can help security personnel notice threats faster in both CCTV video and X-ray screening. The reviewed literature shows that deep detectors, especially real-time YOLO-family models and X-ray-specific methods, achieve useful accuracy, while small objects, occlusion and scarce real data remain challenges. Used as an alert system with human verification and clear policies, weapon detection AI can strengthen public safety.

10.1 Acknowledgment

The authors express their sincere gratitude to the Department of Artificial Intelligence and Data Science, Jaihind College of Engineering, Pune, for providing the facilities, guidance and encouragement needed to carry out this work. The authors also thank the faculty members and colleagues whose valuable suggestions helped improve the quality of this review.

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