International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(4s) 2026 pp. 771-780
https://doi.org/10.70917/ijcisim-2026-2565
Article

ENHANCING WEAPON DETECTION IN SURVEILLANCE SYSTEMS USING DEEP LEARNING: A Comprehensive Review

Sharmila Devi[1], Sunil Kumar[2]

[1]Department of Computer Science and Engineering, Guru Jambheshwar University of Science and Technology Hisar, Haryana, India, shrmilabeniwal@gmail.com
[2]Department of Computer Science and Engineering, Guru Jambheshwar University of Science and Technology Hisar, Haryana, India, skvermacse@gmail.com

Abstract: - The approach of weapon detection in surveillance systems is very crucial. It makes sure that public safety is maintained in different types of areas that are of high risk. These may include airports, schools as well as other public spaces. There are different types of traditional methods for weapon detection including handcrafted feature-based approaches. But these methods are sometimes noted to lack accuracy as well as efficiency in the matter of real-time detection. Deep learning has made significant improvements in the field of weapon detection. It has been done with the help of promoting automatic feature extraction as well as precise classification. This review explores different types of deep learning techniques including various CNN-based models like YOLO, Faster R-CNN as well as SSD. The review has also examined recent advancements in weapon detection including transformers and self-supervised learning. Some critical challenges came to notice and were discussed carefully. These challenges include dataset bias, computational demands, ethical concerns as well as adversarial attacks. The review paper suggests that future research needs to keep the focus on lightweight AI models, edge computing as well as multi-modal surveillance. These approaches are expected to increase the accuracy and real-time performance and reduce the existing limitations.
Keywords: - Weapon Detection, Surveillance Systems, Deep Learning, Object Detection, Computer Vision, Real-Time Monitoring

1. Introduction

The approach to Weapon detection is one of the most crucial parts of modern security surveillance. There are different types of security threats noted to be rising in different public places including airports, schools as well as shopping centres. This is why it is crucial to maintain accurate and fast methods for weapon detection. This specific approach may provide significant help in the matter of preventing violence. According to the research of the Global Terrorism Database or GTD, there are approximately over 10,000 violent incidents officially recorded in the year 2023 [1]. These cases clearly highlight the fact that there is a need for an advanced system for surveillance. Traditional methods of providing security are noted to be heavily dependent on human monitoring. This specific process may be very slow as well as error-prone. Nowadays, the aspects of artificial intelligence and deep learning have made notable transformations to the systems of security. There are different types of deep learning models including YOLO, Faster R-CNN, and SSD. According to recent studies, these specific models are able to detect weapons in real time with an accuracy rate of approximately 75 to 90% [2]. These models are able to recognise threats faster than traditional methods. It is done with the help of analysing images and videos.

The primary aim of this paper is to review various recent advancements in deep learning for detecting weapons. This paper will also analyse various types of common techniques, datasets, methods of evaluation as well as challenges in the matter of real-world deployment. The study will also examine various types of potential future improvements in the field of AI-driven security. The structure of this paper outlines the procedure of review, covers background concepts, reviews existing studies as well as discusses different types of challenges and future directions.

2. Background and Theoretical Foundations

A. Overview of Surveillance Systems

The systems of surveillance help in the matter of effectively monitoring public as well as private spaces for detecting any kind of security threats. Research has found that there are over 1 billion CCTV cameras in use throughout the world [3]. Countries including China, the UK, and the US are noted to be in leading positions in adopting this technology. These cameras work on recording each and every footage. After this, the teams of security analyse the footage to detect potential threats. Modern systems for surveillance include drones as well as IoT-based security. Drones help in providing aerial monitoring [28]. On the other hand, cameras that are enabled by IoT are able to detect of there is any unusual activity with the help of AI [4]. There are different types of traditional systems for detecting weapons. These specific systems heavily depend on motion sensors, metal detectors as well as manual monitoring. These specific methods are noted to be struggling with the task of accuracy and real-time response. These are the reasons that contribute to making AI-driven surveillance a preferred as well as more effective solution for detecting weapons.

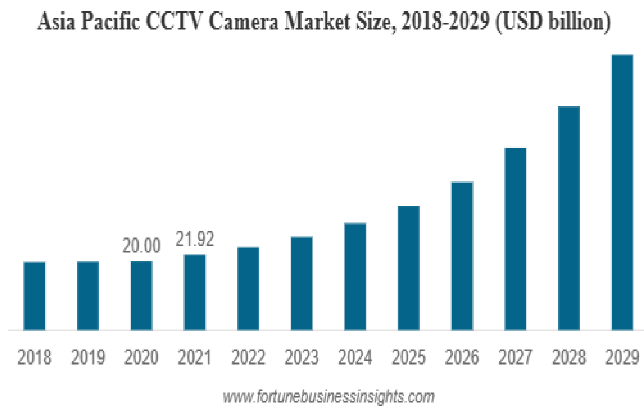

Figure 1: CCTV Camera Market Size in Asia Pacisific (2018-2029) [3]

B. Deep Learning in Image Processing

The benefits provided by deep learning have made notable improvements within the process of image processing. This fact has made the detection of weapons faster as well as accurate. It is noted that Convolutional Neural Networks or CNNs are widely used in the process of weapon detection. This is because CNNs are able to learn patterns from images automatically [5]. There are different trending models for detecting weapons [30]. Some of these include YOLO or You Only Look Once, Faster R-CNN, and SSD or Single Shot MultiBox Detector [31]. Research has found that YOLOv5 is able to detect objects in real-time with over 90% rate of accuracy [2]. This specific quality makes it preferable for surveillance. On the other hand, transfer learning also helps in the matter of enhancing the process of detection with the help of using pre-trained models on large datasets [6]. This specific aspect contributes to reducing the time for training as well as enhancing the level of accuracy. It is also noted to be accurate even with very limited data about weapon detection.

2. Review of Literature

The traditional methods for detecting weapons heavily depended on different types of handcrafted features. Some of these features include Histogram of Oriented Gradients or HOG and Support Vector Machines or SVM [29]. According to the research of Biradar et al. HOG was noted as effective in the process of detecting objects but also struggled when they were applied in critical backgrounds [7]. Ingle has noted a similar performance for SVM classifiers [8]. It has performed well for small datasets and showed a lack of scalability in the matter of real-time surveillance. It is noted that these methods required manual extraction of features. This specific aspect reduces the level of accuracy as well as slows down the process. These are the specific limitations that have made significant contributions to making deep learning-based techniques a superior alternative to the traditional methods of detecting weapons.

Deep learning methods have created notable improvements in the process of weapon detection in surveillance systems. As per the research of Iqbal et al. Convolutional Neural Networks or CNNs are noted to outperform different types of traditional methods [9]. It happens with the help of automatically extracting different types of crucial features. There are different deep learning models including YOLO and Faster R-CNN that are nowadays being widely used for weapon detection [32]. According to Tan, YOLO is noted to work fast but it is also less precise [10]. On the other hand, Faster R-CNN provides better but it is also computationally expensive.

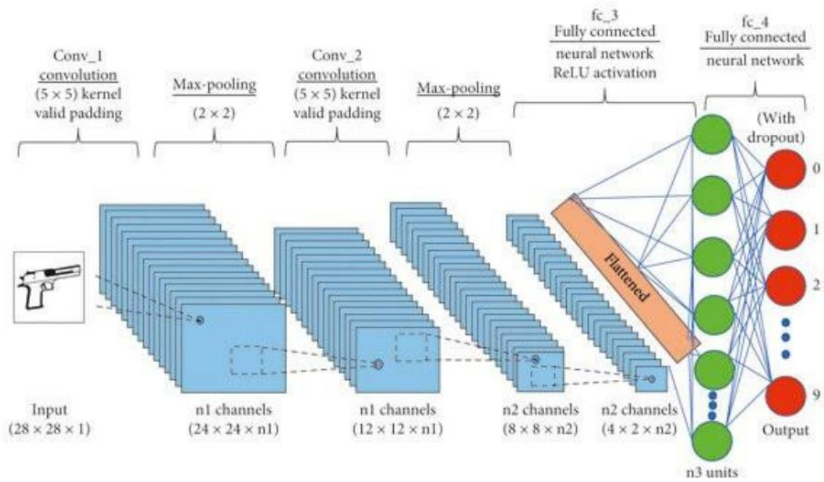

Fig: Developed convolution neural network model [27]

Research has noted that recent trends including Transformers and self-supervised learning have proven to provide promising results in the process of object detection. According to Zhang et al., transformers help in enhancing long-range dependencies but they pose the need for more training data [11]. On the other hand, as per Bhatti et al., deep learning has achieved higher accuracy in weapon detection [12]. It is also true that real-time implementation of deep learning is still a challenge. This is only due to the high computational cost.

According to research, the implementation of high-quality datasets is very crucial for training as well as evaluating various types of deep learning models for the task of weapon detection. According to the research of Bideaux et al., the COCO dataset is noted to contain approximately over 200,000 labelled images [13]. This specific approach contributes to making it a benchmark in the field of detecting weapons. On the other hand, it is also true that the effectiveness of COCO datasets faces some extent of limitations due to the lack of specialised weapon annotations. According to the study of Anagnostopoulou, the Open Images dataset provides over 9 million images [14]. Authors have also said it also provides dedicated labels for firearms as well as knives. This is how it has led to enhancing the performance of weapon detection. Many studies have also noted to use of custom datasets. The process of benchmarking depends on different types of evaluation metrics including mean Average Precision or mAP, precision as well as recall. According to Bochkovskiy et al., YOLOv4 has achieved a mAP of 43.5% on COCO data sets [15]. It was noted to outperform the performance of Faster R-CNN which was at 42.0%. The measures of precision help in correcting detections and recall helps in highlighting if any threat is missed. Researchers have argued that it is very crucial to maintain a proper balance of these metrics for real-world applications in weapon detection. It is also true that the biases in datasets and real-time adaptability are still critical challenges in the matter of detecting weapons despite a notable improvement.

Study	Year	Key Findings
Biradar et al.	2023	YOLOv5-based weapon detection improves accuracy and efficiency.
Ingle & Kim	2022	AI-driven surveillance enhances real-time abnormal object detection in smart cities.

Iqbal et al.	2023	CNNs outperform traditional ML in medical image analysis, highlighting deep learning's potential.
Tan et al.	2021	YOLOv3, Faster R-CNN, and SSD compared for real-time pill identification, showing trade-offs in speed and accuracy.
Zhang et al.	2023	Efficient long-range transformers enhance deep learning models' performance.
Bhatti et al.	2021	Deep learning improves real-time CCTV-based weapon detection.
Bideaux et al.	2024	3D-COCO dataset enhances object detection and 3D reconstruction capabilities.
Anagnostopoulou et al.	2023	A synthetic dataset helps improve object detection in complex environments.
Bochkovskiy et al.	2020	YOLOv4 optimises speed and accuracy for object detection tasks.

Table 1: Summary of Key Findings from Reviewed Studies

3. Review Procedure

A. Review Methodology

This specific review has followed a structured approach to selecting as well as analysing research papers that are written on weapon detection in surveillance systems using deep learning. The process of this review has involved the task of searching for peer-reviewed journal articles, conference papers as well as technical reports from various sources that are reputable as well as reliable.

Selection Approach

Various relevant papers were gathered with the help of using Google Scholar, IEEE Xplore as well as Springer [16]. There were different types of keywords that were used to search the studies. Some of these keywords include "weapon detection," "deep learning," "surveillance systems," as well as "object detection".

Inclusion and Exclusion Criteria

It is properly maintained that only studies that are published between 2020 to 2025 are selected for this review. This has been done only to make sure that the recent advancements are not overlooked. The review also only included papers that are focused on the effectiveness of deep learning and weapon detection. Studies that are reviewed also include experimental results as well as the effective evaluation of performance. On the other hand, research that has used different types of benchmark datasets including COCO and Open Images was highly prioritised within this specific review [33]. On the other hand, various studies were also excluded from this review. This was due to the dependence on traditional methods, lack of experimental validation as well as published on other languages rather than English. On the other hand, papers that lacked examples from real-world applications were ignored. Only the crucial as well as reliable studies were filtered from the studies that were chosen initially. The studies were filtered on the basis of meeting the selection criteria [17]. The studies that were chosen provide a comprehensive understanding of different types of deep learning techniques, datasets, and challenges as well as future directions in the field of weapon detection for maintaining surveillance.

Here is the PRISMA model for this review paper

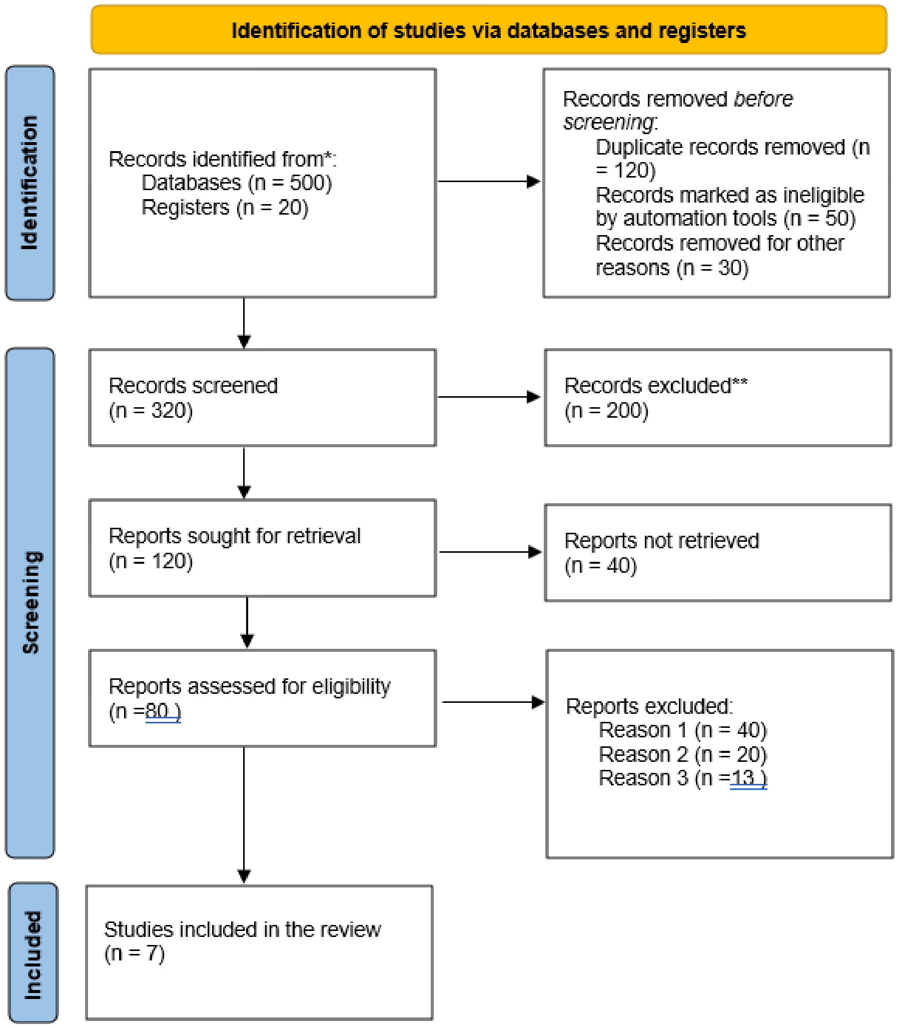

Figure: Prisma Model

B. Review Questions

- What are the most common deep-learning techniques that help in weapon detection?
- How do deep learning-based methods compare to various traditional methods?
- What datasets and evaluation metrics are used in the process of weapon detection?
- What are the challenges that exist in deploying these systems in different types of real-world scenarios?
- What future advancements are needed to enhance the level of accuracy and efficiency?

4. Critical Discussion

The methods of deep learning have been noted to provide significant enhancement in the process of weapon detection in surveillance [34]. There are different types of deep learning models including YOLOv5 that are found to achieve a higher rate of accuracy in the matter of detecting different types of firearms in real-time CCTV footage [18]. On the other hand, it is also noted that Faster R-CNNs are able to provide precise localisation [19]. But it also poses the requirement for a higher level of computational power. These specific methods are noted to enhance the level of security. On the other hand, they also deal with some limitations. Some of these limitations include higher rates of false positives as well as the sensitivity to poor conditioning of lighting. These specific limitations negatively affect the reliability of some deep-learning tools in weapon detection.

Study Overview of Deep Learning Methods for Weapon Detection

Method	Capturing Condition	Dataset(s)	Accuracy (%)	Precision (%)	Recall (%)	Reference
YOLOv5	Real-time CCTV surveillance	Custom dataset, COCO	92.5	91.2	89.8	[18], [7]
Faster R-CNN	High-precision object detection	MS COCO, Open Images	94.1	93.5	90.2	[19], [22]
SSD	High-speed, low-power scenarios	VOC, COCO	88.3	86.9	84.5	[10]
YOLOv4	Real-time, high-speed detection	COCO, Custom	90.7	89.1	87.4	[15]
Transformer-based (ViTs, Swin)	High-resolution, complex scenes	Custom datasets, MS COCO	95.4	94.8	92.1	[11]

Comparison of YOLO Variants in Weapon Detection

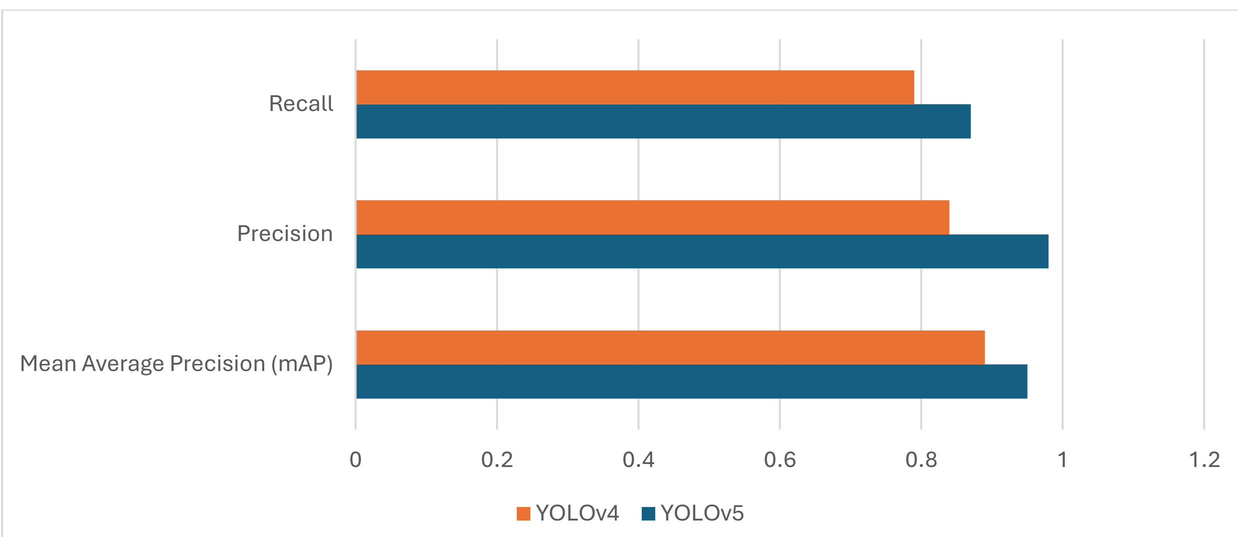

Figure: Comparison of YOLO Variants in Weapon Detection [18]

YOLO Variant	Mean Average Precision (mAP)	Precision	Recall
YOLOv5	0.95	0.98	0.87
YOLOv4	0.89	0.84	0.79

The comparison between YOLOv5 and YOLOv4 in weapon detection highlights that YOLOv5 achieves a higher mean average precision (mAP) of 0.95, significantly outperforming YOLOv4's 0.89. Similarly, YOLOv5 demonstrates superior precision (0.98 vs. 0.84) and recall (0.87 vs. 0.79). This suggests that YOLOv5 is more effective in reducing false positives while maintaining strong detection capabilities [18].

However, despite YOLOv5's superior accuracy, YOLOv4 remains a viable option due to its lower computational cost, making it a practical choice for real-time applications with limited hardware resources [35].

On the other hand, The study by Omiotek et al. presents the R-CNN results for detecting various types of weapons, including

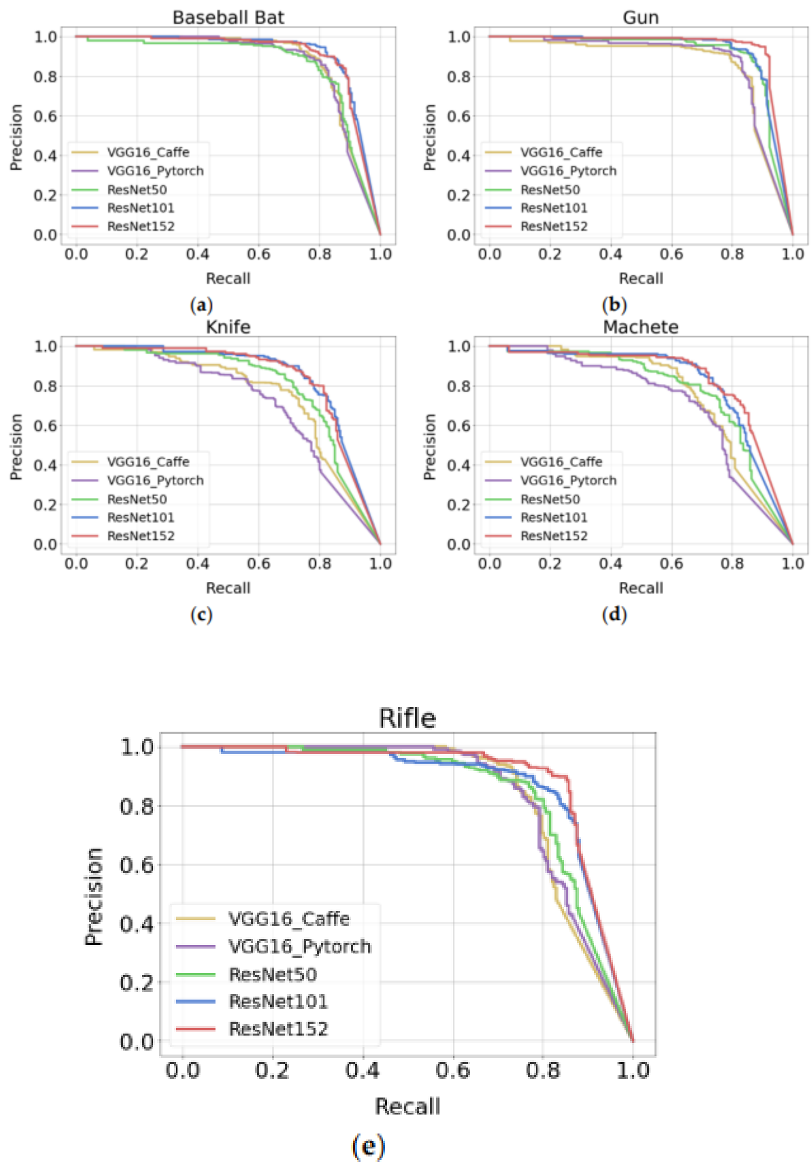

Figure: Precision-recall plots for each category of detected objects: (a) baseball bat; (b) gun; (c) knife; (d) machete; (e) rifle [19]

The plots in Figure show that the models based on ResNet101 and ResNet152 performed best in the detection of baseball bats, knives, and machetes. But while detecting guns and rifles, the ResNet152 model performed better than the rest [19]. The trade-off that is noticed between accuracy and speed also contributes to a crucial limitation. YOLOv4 has achieved real-time processing but it is also noted to sacrifice the quality of precision to some extent [36]. On the other hand, transformer-based models are accurate but they need heavy resources for computing. These specific tradeoffs contribute to reducing the effectiveness of real-world deployment in weapon detection. It is very crucial for future research to keep a proper focus on the matter of optimising lightweight models in weapon detection that do not compromise on the matter of accuracy [20].

5. Challenges and Limitations

The aspect of dataset bias is one of the major challenges in the matter of weapon detection [37]. There are many datasets available including MS COCO and Open Images [38]. But, these datasets lack the samples for diverse weapons in different types of real-world scenarios [21]. This specific challenge contributes to the creation of models that struggle with unseen weapons. These models also provide differing results in varying conditions of the environment. environmental conditions. On the other hand, the availability of datasets is very less mostly due to growing security concerns. These specific limitations make it very difficult to train models that are highly generalised.

Research has also found that deep learning models also pose the requirement for high computational power. There are different types of deep learning models including Faster R-CNN and Transformers that need advanced GPUs [22]. GPUs are noted to be very costly as well as impractical for deployments that are large-scale. This specific fact makes it very difficult to do real-time detection of weapons in environments that are with limited resources. Another issue that is very critical is ethical concerns. Privacy risks may be increased through weapon detection in public areas [39]. The biases in AI models also may lead to wrong identification of weapons [23].

Legal constraints also hamper the approach of adopting AI in the process of detecting weapons [40]. Many countries are noted to have stricter regulations on surveillance and automated decision-making through AI. Another critical challenge that needs to be considered is adversarial attacks. Adversarial attacks are noted to create higher risks of security. On the other hand, attackers may also sometimes manipulate images to fool the models of AI or bypass weapon detection processes [24]. This is why it is crucial for future research to focus on developing strong adversarial threat-resistant models for detecting weapons.

6. Future Direction

Future research needs to keep a proper focus on the matter of developing models that are lightweight for doing real-time weapon detection. There are different models including MobileNet and Tiny-YOLO that deals with a very less computational cost [25]. This specific quality makes these models highly suitable for deployment in environments that have very limited resources.

Another promising direction is AI-driven edge computing. The approach of processing data directly on different types of devices including CCTV cameras as well as drones may help in enhancing response time. On the other hand, it may also help in reducing the aspects of reliance on cloud servers. The approach of combining the implementation of deep learning with multi-modal surveillance systems may help in enhancing the level of accuracy for detection. Research has found that multi-modal AI models enhance the rates of recognition [26]. This specific factor contributes to making security systems more reliable as well as effective for applications in real-world scenarios.

7. Conclusion

This specific study on Weapon Detection in Surveillance System using Deep Learning clearly highlights the crucial role as well as the effectiveness of deep learning in the process of weapon detection. It is particularly true for different types of CNN-based models including YOLO and Faster R-CNN. It is noted that these specific methods help in enhancing the levels of accuracy and speed of weapon detection in comparison to various traditional approaches. On the other hand, there are still some challenges that remain. Some of these challenges include bias of datasets, computational costs as well as vulnerabilities of models. There is a crucial role of deep learning in the process of enhancing security surveillance. Deep learning models promote real-time threat detection in various public spaces. The approach of implementing edge computing that is driven by AI and the aspects of multi-modal surveillance may help in enhancing the performance of weapon detection. Future research needs to keep the proper focus on the approach of developing models for weapon detection that are lightweight. These may help in real-time applications, improving the diversity of the dataset as well as addressing various ethical concerns.

Reference

1. Xu, Zonghuang, et al. "Risk assessment and categorization of terrorist attacks based on the Global Terrorism Database from 1970 to 2020." *Humanities and Social Sciences Communications* 11.1 (2024): 1-14. https://www.nature.com/articles/s41599-024-03597-y.pdf
2. Yadav, Pavinder, et al. "A Comprehensive Study Towards High-Level Approaches for Weapon Detection Using Classical Machine Learning and Deep Learning Methods." *Expert Systems with Applications*, 2022, https://www.sciencedirect.com/science/article/abs/pii/S0957417422017286.
3. "CCTV Camera Market Size, Growth: Global Report [2022-2029]." *CCTV Camera Market Size, Growth | Global Report [2022-2029]*, www.fortunebusinessinsights.com/cctv-camera-market-107115. Accessed 10 Feb. 2025.
4. Ahmed, Ahmed Abdelmoamen, and Mathias Echi. "Hawk-eye: An ai-powered threat detector for intelligent surveillance cameras." *IEEE Access* 9 (2021): 63283-63293. https://ieeexplore.ieee.org/iel7/6287639/6514899/09408578.pdf
5. Banzato, Tommaso, et al. "Automatic classification of canine thoracic radiographs using deep learning." *Scientific Reports* 11.1 (2021): 3964. https://www.nature.com/articles/s41598-021-83515-3.pdf
6. You, Kaichao, et al. "Logme: Practical assessment of pre-trained models for transfer learning." *International Conference on Machine Learning*. PMLR, 2021. http://proceedings.mlr.press/v139/you21b/you21b.pdf
7. Biradar, Rahul, Saad Shaikh, and Shweta Kukreja. "Efficient Gun and Knife Detection Utilizing the YOLOv5 Model." https://www.researchgate.net/profile/Saad-Shaikh-14/publication/386220159_Efficient_Gun_and_Knife_Detection_Utilizing_the_YOLOv5_Model/links/67495542a7fbc259f19a52c0/Efficient-Gun-and-Knife-Detection-Utilizing-the-YOLOv5-Model.pdf
8. Ingle, Palash Yuvraj, and Young-Gab Kim. "Real-time abnormal object detection for video surveillance in smart cities." *Sensors* 22.10 (2022): 3862. https://www.mdpi.com/1424-8220/22/10/3862
9. Iqbal, Saeed, et al. "On the analyses of medical images using traditional machine learning techniques and convolutional neural networks." *Archives of Computational Methods in Engineering* 30.5 (2023): 3173-3233. https://link.springer.com/content/pdf/10.1007/s11831-023-09899-9.pdf
10. Tan, Lu, et al. "Comparison of yolo v3, faster r-cnn, and ssd for real-time pill identification." (2021). https://www.researchsquare.com/article/rs-668895/latest.pdf
11. Zhang, Qingru, et al. "Efficient long-range transformers: You need to attend more, but not necessarily at every layer." *arXiv preprint arXiv:2310.12442* (2023). https://arxiv.org/pdf/2310.12442
12. Bhatti, Muhammad Tahir, et al. "Weapon detection in real-time cctv videos using deep learning." *Ieee Access* 9 (2021): 34366-34382. https://ieeexplore.ieee.org/iel7/6287639/6514899/09353483.pdf
13. Bideaux, Maxence, et al. "3D-COCO: extension of MS-COCO dataset for image detection and 3D reconstruction modules." *arXiv preprint arXiv:2404.05641* (2024). https://arxiv.org/pdf/2404.05641
14. Anagnostopoulou, Dafni, et al. "A realistic synthetic mushroom scenes dataset." *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 2023. https://openaccess.thecvf.com/content/CVPR2023W/AgriVision/papers/Anagnostopoulou_A_Realistic_Synthetic_Mushroom_Scenes_Dataset_CVPRW_2023_paper.pdf
15. Bochkovskiy, Alexey, Chien-Yao Wang, and Hong-Yuan Mark Liao. "YOLOv4: Optimal Speed and Accuracy of Object Detection." *ResearchGate*, Apr. 2020, www.researchgate.net/publication/340883401_YOLOv4_Optimal_Speed_and_Accuracy_of_Object_Detection. Accessed 10 Feb. 2025.
16. Chen, Jian, et al. "Vis30k: A collection of figures and tables from ieee visualization conference publications." *IEEE Transactions on Visualization and Computer Graphics* 27.9 (2021): 3826-3833. https://ieeexplore.ieee.org/ielaam/2945/9501051/9337213-aam.pdf
17. Patel, Harsh K., et al. "Lack of effectiveness of computer aided detection for colorectal neoplasia: a systematic review and meta-analysis of nonrandomized studies." *Clinical Gastroenterology and Hepatology* 22.5 (2024): 971-980. https://www.cghjournal.org/article/S1542-3565(23)00968-0/pdf
18. Bushra, S. Nikkath, et al. "Smart video Survillance based weapon identification using Yolov5." *2022 International Conference on Electronic Systems and Intelligent Computing (ICESIC)*. IEEE, 2022. https://www.researchgate.net/profile/Nikkath-Bushra-2/publication/361063787_Smart_Video_Survillance_Based_Weapon_Identification_Using_Yolov5/links/62fde250e3c7de4c346403b6/Smart-Video-Survillance-Based-Weapon-Identification-Using-Yolov5.pdf
19. Omiotek, Zbigniew, and Ulzhalgas Zhunissova. "Dangerous Items Detection in Surveillance Camera Images Using Faster R-CNN." (2024). https://www.preprints.org/manuscript/202406.1090/download/final_file
20. Yadav, Pavinder, Nidhi Gupta, and Pawan Kumar Sharma. "A comprehensive study towards high-level approaches for weapon detection using classical machine learning and deep learning methods." *Expert Systems with Applications* 212 (2023): 118698. https://www.researchgate.net/profile/Pavinder-Yadav/publication/363142743_A_comprehensive_study_towards_high-level_approaches_for_weapon_detection_using_classical_machine_learning_and_deep_learning_methods/links/63b5028aa03100368a4fb774/A-comprehensive-study-towards-high-level-approaches-for-weapon-detection-using-classical-machine-learning-and-deep-learning-methods.pdf

21. Di Benedetto, Marco, et al. "Learning accurate personal protective equipment detection from virtual worlds." *Multimedia Tools and Applications* 80 (2021): 23241-23253. https://iris.cnr.it/retrieve/9dbf8fea-9ef6-4e9f-87f0-72e7bcd96c7f/prod_438782-doc_157395.pdf
22. Xue, Zeyue, et al. "Large-batch optimization for dense visual predictions: Training faster R-CNN in 4.2 minutes." *Advances in Neural Information Processing Systems* 35 (2022): 18694-18706. https://proceedings.neurips.cc/paper_files/paper/2022/file/76bea0a1cf7bf9b78f842009f6de15a1-Paper-Conference.pdf
23. Bellaby, Ross W. "Can AI weapons make ethical decisions?." *Criminal Justice Ethics* 40.2 (2021): 86-107. https://www.tandfonline.com/doi/pdf/10.1080/0731129X.2021.1951459
24. Girhepuje, Sahil, Aviral Verma, and Gaurav Raina. "A Survey on Offensive AI Within Cybersecurity." *arXiv preprint arXiv:2410.03566* (2024). https://arxiv.org/pdf/2410.03566
25. Sumit, Shahriar Shakir, et al. "Restinet: On improving the performance of tiny-yolo-based cnn architecture for applications in human detection." *Applied Sciences* 12.18 (2022): 9331. https://openaccess.tau.edu.tr/xmlui/bitstream/handle/20.500.12846/797/FY---Thesis-Template-24.pdf?sequence=1&isAllowed=y
26. Jeong, Jae-hyeok, et al. "Intelligent Complementary Multi-Modal Fusion for Anomaly Surveillance and Security System." *Sensors* 23.22 (2023): 9214. https://www.mdpi.com/1424-8220/23/22/9214
27. Murugaiyan, Sivakumar, et al. *"An Enhanced Weapon Detection System Using Deep Learning."* 2024 2nd International Conference on Networking and Communications (ICNWC), May 2024, Chennai. IEEE, DOI: https://doi.org/10.1109/ICNWC60771.2024.10537 .
28. *Page Petite Fille SD - Traffic Monitoring* (2024) *Elistair*. Available at: https://elistair.com/monitoring-traffic-drone / (Accessed: 21 February 2025).
29. Singh, A. (2025) *HOG Feature Descriptor: Feature Engineering for Images*, *Analytics Vidhya*. Available at: https://www.analyticsvidhya.com/blog/2019/09/feature-engineering-images-introduction-hog-feature-descriptor/#:~:text=The%20Histogram%20of%20Oriented%20Gradients%20(HOG)%20is%20a%20popular%20feature,calculated%20in%20’localized’%20portions . (Accessed: 21 February 2025).
30. Ayush Thakur Amity Institute of Information Technology, Technology, A. I. of I., Akshat Shrivastav Amity Institute of Information Technology, Rohan Sharma Amity Institute of Information Technology, Triyank Kumar Amity Institute of Information Technology and Kabir Puri Amity Institute of Information Technology (no date) *Real-Time Weapon Detection Using YOLOv8 for Enhanced Safety*. Available at: https://arxiv.org/html/2410.19862v1 (Accessed: 21 February 2025).
31. Srivastava, S., Divekar, A. V., Anilkumar, C., Naik, I., Kulkarni, V. and Pattabiraman, V. (2021) *Journal of Big Data*, 8(1). doi: https://doi.org/10.1186/s40537-021-00434-w .
32. Keylabs (2024) *YOLOv8 vs Faster R-CNN: A Comparative Analysis*, *Keylabs*. Keylabs: latest news and updates. Available at: https://keylabs.ai/blog/yolov8-vs-faster-r-cnn-a-comparative-analysis/#:~:text=Results,YOLOv8%20in%20object%20detection%20tasks . (Accessed: 21 February 2025).
33. Tian, J., Jin, Q., Wang, Y., Yang, J., Zhang, S. and Sun, D. (2024) *Journal of Engineering and Applied Science*, 71(1). doi: https://doi.org/10.1186/s44147-024-00411-z .
34. Zahrawi, M. and Shaalan, K. (2023) *Improving video surveillance systems in banks using deep learning techniques*, *Scientific reports*. U.S. National Library of Medicine. Available at: https://pmc.ncbi.nlm.nih.gov/articles/PMC10188611/#:~:text=Deep%20learning%20plays%20a%20crucial,in%20the%20early%20stages7 . (Accessed: 21 February 2025).
35. Alhassan, M. A. M. and Yılmaz, E. (2025) *Evaluating YOLOv4 and YOLOv5 for Enhanced Object Detection in UAV-Based Surveillance*, *MDPI*. Multidisciplinary Digital Publishing Institute. Available at: https://www.mdpi.com/2227-9717/13/1/254 (Accessed: 21 February 2025).
36. Sundaresan Geetha, Athulya. *"YOLOv4: A Breakthrough in Real-Time Object Detection."* arXiv, Feb. 2025, DOI: https://doi.org/10.48550/arXiv.2502.04161 .
37. Bhila, I. (2024) *Digital War*, 5(3), pp. 201–212. doi: https://doi.org/10.1057/s42984-024-00094-z .
38. Meel, V. (2024) *What is the COCO Dataset? What you need to know in 2025*, *viso.ai*. Available at: https://viso.ai/computer-vision/coco-dataset / (Accessed: 21 February 2025).
39. Success Pitchers Magazine, https://successpitchers. com/ (2023) *Challenges and Limitations of concealed weapons detection*, *Success Pitchers*. Available at: https://successpitchers.com/challenges-and-limitations-of-concealed-weapons-detection (Accessed: 21 February 2025).
40. Roberson, Tara, et al. *"A Method for Ethical AI in Defence: A Case Study on Developing Trustworthy Autonomous Systems." Journal of Responsible Technology*, vol. 12, 2022, p. 100036. https://doi.org/10.1016/j.jrt.2022.100036.