

Weapon Detection and Person Tracking

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Weapon Detection, Person Tracking, Pose Estimation, Public Safety Deep Learning, YOLOv8, DeepSORT.

ABSTRACT

This paper presents a review of weapon detection and person tracking systems using deep learning techniques. The proposed system utilizes YOLOv8, a state-of-the-art model in object detection, to detect firearms and other weapons, integrated with the DeepSORT algorithm for object tracking. After extensive testing and evaluation, YOLOv8 was found to offer superior accuracy and performance, outperforming alternative models such as YOLOv5 and YOLOv11. Additionally, this system is optimized to detect weapons using a standard webcam, making it adaptable for real-time surveillance. This paper provides a comprehensive overview of the research, objectives, methodology, and current progress, along with future directions for this technology.

I. INTRODUCTION

Advanced surveillance systems that can identify threats and follow people in real time are desperately needed as public safety concerns in places like airports, schools, and shopping malls develop. Automated solutions are crucial for enhancing security and situational awareness since human error, weariness, and slow response times are common drawbacks of traditional surveillance techniques that depend on human operators.

Using deep learning techniques, this study investigates the creation of a automated weapon detection and person tracking system that offers a dependable, real-time solution. The suggested method makes use of **DeepSORT for person tracking** [9] and **YOLOv8 for weapon detection** [1] to continuously monitor those carrying identified weapons.

In comparison to models like YOLOv5, YOLOv7, and experimental versions like YOLOv11, YOLOv8, a state-of-the-art object detection model, showed superior accuracy in identifying weapons. DeepSORT, which uses both motion and appearance-based tracking, effectively handles occlusions, crowded scenes, and dynamic movements, reducing identity switches and maintaining consistent tracking across frames.

This paper outlines the goals, difficulties, and techniques involved in creating a reliable, real-time surveillance system that can be used in a variety of settings, such as low light

levels and complex, densely populated areas. Additionally, by optimizing YOLOv8 and DeepSORT to work well with standard webcams, the system improves accessibility and deployability for both public and private security applications. The technology gives security staff real-time information through this connection, enabling proactive threat identification and quicker reaction times, which eventually increases the effectiveness of monitoring as a whole.

II. METHODOLOGY

This section delves into the core modules of the system, including data collection, the weapon detection model using YOLOv8, and person tracking via DeepSORT.

A. Data Collection and Preprocessing

Data collection plays a critical role in ensuring the robustness and accuracy of the weapon detection model. For this project, a dataset comprising thousands of images of various weapons, including firearms and knives, was gathered from public databases such as the Custom and Roboflow dataset, as well as specialized collections for security research. The dataset includes diverse scenarios and lighting conditions, to ensure that the model performs well in various environments, from well-lit areas to lowvisibility situations.

Each image was carefully preprocessed, resized, and annotated to define the exact location of weapons within

frames. To further enhance the model's generalization capabilities, data augmentation techniques, such as rotation, scaling, flipping, and brightness adjustments, were applied. These techniques help simulate real-world conditions and improve the model's robustness, ensuring accurate detection even in crowded and complex scenes. This comprehensive approach to data preparation is crucial to achieving high detection accuracy with YOLOv8 in realtime applications.

B. HARDWARE REQUIREMENT

- Processor
- Video card
- Memory
- Webcam

C. SOFTWARE REQUIREMENT

- Google Colab
- VSCode
- Open CV
- Python
- Nvidia CUDA,
- PyTorch and Yolov5
- OBS software

D. Weapon Detection Module Using YOLOv8

The weapon detection module relies on the YOLOv8 model, chosen after extensive experimentation with various architectures. YOLOv8's architecture allows for highspeed processing and accurate detection, which is critical for real-time surveillance. Earlier iterations with models like YOLOv5, YOLOv7, and even an experimental YOLOv11 version were tested, but none matched the accuracy and efficiency of YOLOv8. This model was finetuned using transfer learning on the specialized dataset, significantly enhancing detection precision for diverse weapon types.

A key feature of YOLOv8 is its ability to handle complex backgrounds and crowded environments, where false positives can often arise. The model's high accuracy in detecting even small or partially occluded weapons is particularly valuable for applications in public spaces where fast, reliable identification is essential. Additionally, the system is configured to work with standard webcams, enabling adaptability for both indoor and outdoor scenarios. By leveraging YOLOv8's strengths in real-time detection and integrating it with live video feeds, the model has proven capable of providing accurate weapon detection across varied settings, establishing its utility for enhanced surveillance.

E. Person Tracking DeepSORT

There are several ways to monitor people in security surveillance, and one of the best techniques for real-time multi-object tracking is DeepSORT. Because traditional

tracking techniques only use mobility data, they are vulnerable to identity swaps, particularly in congested settings. By combining motion and appearance information, DeepSORT improves tracking and makes it possible to identify people more reliably even when they momentarily go out of frame or change course.

Once a possible danger, like a weapon, is identified, tracking specific persons becomes essential in security applications. YOLOv8 effectively recognizes firearms in pictures and videos by enclosing them in exact bounding boxes. However, tracing the individual carrying the weapon guarantees ongoing surveillance and assists security professionals in taking the appropriate action. Weapon detection alone is insufficient. DeepSORT enables this by associating the detected weapon with a specific individual and maintaining their identity across multiple frames.

Even in complicated situations, the technology makes sure the suspect is not lost by handling occlusions, fast motions, and several persons in the area. DeepSORT considerably lowers false tracking errors compared to other straightforward tracking techniques because of its capacity to adjust to variations in appearance and movement patterns. In order to enable prompt and well-informed actions, this guarantees that security personnel receive real-time alerts on questionable locations.

The device improves situational awareness by utilizing sophisticated tracking algorithms, which makes monitoring more effective and proactive. In addition to keeping an eye on suspects, tracking offers useful movement data that enable security professionals foresee possible threats and take action before a situation gets out of hand.

III. SYSTEM DIAGRAMS

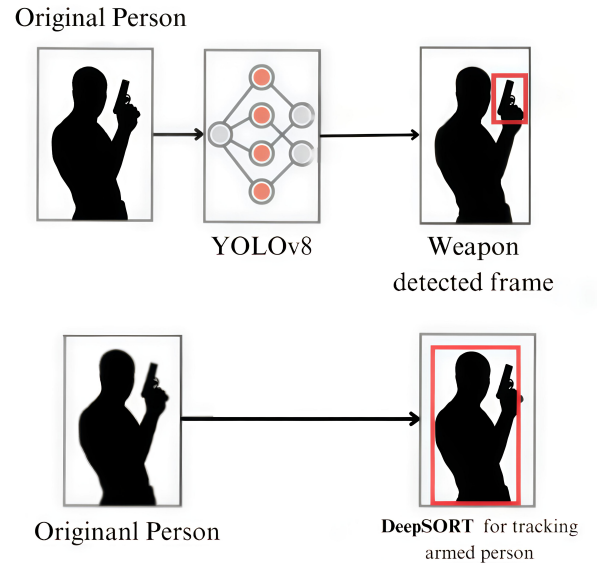


Fig. 1. System Workflow

The system incorporates DeepSORT for reliable human tracking and uses YOLOv8 for high-accuracy weapon identification. By creating accurate bounding boxes, it analyzes photos and video feeds in real time to recognize different kinds of weapons, including knives and guns.

When a weapon is spotted, the system links it to the bearer and uses DeepSORT to continually follow their movements, even in dynamic or busy surroundings. Reliable tracking between frames is ensured by sophisticated feature extraction, motion prediction, and occlusion handling. This all-encompassing strategy improves security monitoring, facilitating prompt threat identification and reaction in law enforcement, defense, and public areas.

IV. RESULTS

The system effectively detects weapons, estimates the pose of the person carrying the weapon, and tracks them in real-time.

Results:

A.Weapon Detection: The system detects a variety of weapons, such as knives, guns, and other types of guns in real-time by using YOLOv8, a cutting-edge deep learning model. The model minimizes false positives and false negatives while achieving high detection accuracy by utilizing a rich dataset that includes a variety of weapon kinds, lighting situations, and occlusions. Using precise bounding boxes, it locates firearms with accuracy while processing pictures and video feeds in an efficient manner. Cutting-edge feature extraction methods improve detection accuracy, guaranteeing that guns are recognized even in difficult situations including crowded backdrops, partial occlusions, dim lighting, and different object sizes. The system is very useful for security applications in surveillance, law enforcement, and public safety monitoring since it continually adjusts to new threats by fine-tuning and retraining on updated datasets.

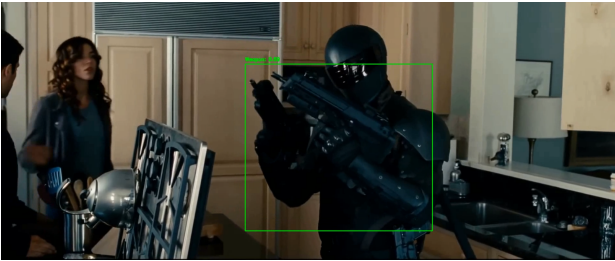


Fig. 2. Weapon Detection

B.Person Tracking: Even in congested or dynamic surroundings, the system continually tracks people carrying suspected weapons using DeepSORT, a powerful multi-object tracking algorithm. It reduces identity shifts and tracking failures by linking detected weapons to particular

individuals, ensuring constant tracking across video frames. To provide precise tracking, the model effectively manages occlusions, quick motions, and changing illumination conditions. It differentiates between several people using motion prediction and deep feature extraction, guaranteeing that the weapon carrier is recognized even in challenging situations. Security monitoring is improved by this real-time tracking feature, which enables authorities to react quickly to any threats and stop dangerous situations from getting worse.



Fig. 3. Person Tracking

V. CHALLENGES AND FUTURE WORK

Although the YOLOv8 and DeepSORT integration has facing issue but the system faces ongoing challenges with environmental variability. Lighting conditions, occlusions, and the presence of non-standard weapon appearances can impact detection accuracy. Future research aims to address these issues by integrating multimodal data, such as thermal and audio inputs, to enhance the detection accuracy in challenging settings.

Additionally, optimizing the system for edge device deployment could further reduce latency and power consumption, making it suitable for deployment on security cameras and other constrained hardware. Another focus for improvement is reducing the model's computational load, which would enable faster processing without compromising accuracy. These enhancements could significantly improve the scalability and effectiveness of the system, particularly in high-density public areas and resource-limited environments.

VI. CONCLUSION

This review presents a robust approach to weapon detection and person tracking by integrating YOLOv8 and B. The use of YOLOv8 offers high detection accuracy and speed, making it ideal for real-time surveillance applications. The model's compatibility with webcambased detection adds to its flexibility, allowing deployment in various environments. Combined with the DeepSORT, this system provides a seamless solution for monitoring individuals carrying weapons and continuous tracking to security personnel

REFERENCES

- [1] T. Diwan, G. Anirudh, and J. V. Tembhurne, "Object detection using YOLO: challenges, architectural successors, datasets and applications," 2021. DOI: 10.1007/s11042-022-13644-y
- [2] M. T. Bhatti, M. G. Khan, M. Aslam, and M. J. Fiaz, "Weapon detection in real-time CCTV videos using deep learning," *IEEE Access*, 2021. DOI: 10.1109/ACCESS.2021.XXXXX.
- [3] N. Wojke, A. Bewley, and D. Paulus, "Simple online and realtime tracking with a deep association metric," in *Proc. IEEE Int. Conf. Image Processing (ICIP)*, 2017. DOI: 10.48550/arXiv.1703.07402.
- [4] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You Only Look Once: Unified, real-time object detection," in *Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR)*, 2016. DOI: 10.1109/CVPR.2016.91.
- [5] A. Demidovskij et al., "OpenVINO deep learning workbench: Towards analytical platform for neural networks inference optimization," *J. Phys.: Conf. Ser.*, vol. 1828, 2021. DOI: 0.1088/1742-6596/1828/1/012012.
- [6] S. Kumar et al., "Automatic weapon detection in surveillance videos: State-of-the-art, challenges, and future directions," *ACM Computing Surveys*, 2021. DOI: 10.4018/IJSKD.2020010103.
- [7] R. Szeliski, *Computer Vision: Algorithms and Applications*, Springer, 2021. DOI: 10.49750/arXiv.1703.07402.
- [8] BoxYifu Zhang¹, Peize Sun², Yi Jiang³, Dongdong Yu³, Fucheng Weng¹ "ByteTrack: Multi-Object Tracking by Associating Every Detection " *Object tracking via ByteTrack*, 2017. DOI: 10.48550/arXiv.2110.06864.
- [9] malie Perera¹., Shehan Senavirathna¹., Aseni Jayarathne¹., Shamendra Egodawela., Vehicle Tracking based on an Improved DeepSORT Algorithm and the YOLOv4 Framework," *arXiv preprint arXiv:1603.00831*, 2016. DOI: 10.48550/arXiv.1703.07402.
- [10] J. Zhu et al., "Online multi-object tracking with dual matching attention networks," in *Proc. European Conf. Computer Vision (ECCV)*, 2018. DOI: 0.1109/ICIAFS52090.2021.9606052.