Weapon Detection and Person Tracking

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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 Bytetrack algorithm for multi-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.

Index Terms—Weapon Detection, Person Tracking, Deep Learning, YOLOv8, Bytetrack, Real-Time Surveillance, Public Safety

I. Introduction

With increasing concerns over public safety in environments such as airports, schools, and shopping centers, there is a critical need for advanced surveillance systems that can reliably detect weapons and track individuals in real-time. Traditional surveillance methods relying on human operators are limited by potential fatigue, human error, and delays in response. In response, this study explores the development of an automated weapon detection and person tracking system, leveraging deep learning techniques to provide a real-time, reliable solution.

The proposed system integrates YOLOv8, a cutting-edge object detection model, with the DeepSORT tracking algorithm. Through extensive testing, YOLOv8 demonstrated the highest accuracy in detecting weapons, outperforming models such as YOLOv5, YOLOv7, and even experimental versions like YOLOv11. This paper highlights the objectives, challenges, and methodologies undertaken to create a robust, real-time surveillance solution capable of adapting to diverse environments and challenges, such as low lighting and crowded scenes. By optimizing YOLOv8 to operate with a standard webcam, this system enhances the accessibility and deployability of AI-powered surveillance, with potential applications in both public and private security sectors.

II. Research Elaboration

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 low-visibility 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 real-time applications.

B. 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 high-speed 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 fine-tuned 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.

C. Person Tracking and System Integration Using ByteTrack

To enhance weapon detection capabilities, ByteTrack is employed to track individuals in real-time following the identification of a weapon. ByteTrack is particularly effective for multi-object tracking, as it utilizes both motion information and appearance features to accurately follow individuals across frames, ensuring reliable identification and reducing the occurrence of ID switches. This tracking functionality is essential for monitoring individuals who may be carrying weapons, as it allows security personnel to keep a continuous watch on suspects' movements, even in crowded environments where individuals might be momentarily obscured or change directions.

Integrating YOLOv8 with ByteTrack creates a seamless, end-to-end system that triggers alerts when a weapon is detected and proceeds to track the individual in real time. The system continuously updates security personnel on the individual's location, allowing for rapid and informed responses. This combination enhances situational awareness and enables a proactive approach to security by equipping teams with real-time movement insights, allowing them to anticipate suspects' movements and prepare appropriate responses. This integrated system thus adds significant value to security operations by enabling more dynamic and responsive threat management.

Fig. 2. Current Model Results showing YOLOv8 detection accuracy

III. System Diagrams and Results

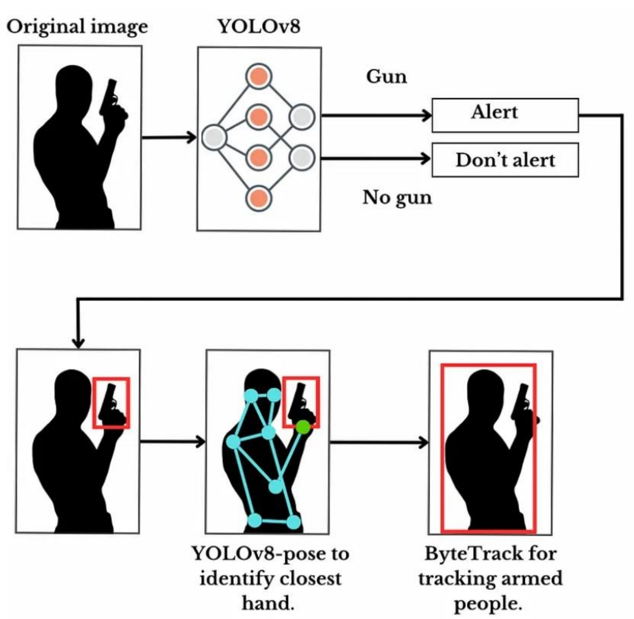

Fig. 1. System Block Diagram of Weapon Detection and Person Tracking using YOLOv8 and ByteTrack

Figure 1 provides a comprehensive system block diagram illustrating the end-to-end workflow, from data input through weapon detection and person tracking, to the alert system. Figure 2 shows preliminary results demonstrating the superior accuracy achieved with YOLOv8 for weapon detection and the stability of DeepSORT in tracking individuals in real-time. These results underscore the potential for this system in practical surveillance applications, delivering reliable, actionable intelligence to enhance public safety.

IV. Challenges and Future Work

Although the YOLOv8 and DeepSORT integration has proven effective, 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.

V. 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 webcam-based detection adds to its flexibility, allowing deployment in various environments. Combined with the Bytetrack, this system provides a seamless solution for monitoring individuals carrying weapons, delivering timely alerts and continuous tracking to security personnel.

Future work will focus on optimizing the system for diverse environmental conditions and exploring additional sensor inputs for greater resilience and accuracy. By refining these components, this AI-driven system shows great potential for enhancing public safety, offering a scalable and proactive solution for modern surveillance needs.

References

1. T. Diwan, G. Anirudh, and J. V. Tembhurne, ”Object detection using YOLO: challenges, architectural successors, datasets and applications,” 2021.

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.

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.

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.

5. A. Demidovskij et al., ”OpenVINO deep learning workbench: Towards analytical platform for neural networks inference optimization,” *J. Phys.: Conf. Ser.*, vol. 1828, 2021.

6. A. S. V. Rao, S. Kainth, A. Bhattacharya, and T. Amgoth, ”An efficient weapon detection system using NSGCU-DCNN classifier in surveillance,” *Journal of Surveillance Systems*, 2021.

7. S. Kumar et al., ”Automatic weapon detection in surveillance videos: State-of-the-art, challenges, and future directions,” *ACM Computing Surveys*, 2021.

8. R. Szeliski, *Computer Vision: Algorithms and Applications*, Springer, 2021.

9. S. Ren, K. He, R. Girshick, and J. Sun, ”Faster R-CNN: Towards real-time object detection with region proposal networks,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2017.

10. A. Milan, L. Leal-Taixé, et al., ”MOT16: A benchmark for multi-object tracking,” *arXiv preprint arXiv:1603.00831*, 2016.

11. J. Zhu et al., ”Online multi-object tracking with dual matching attention networks,” in *Proc. European Conf. Computer Vision (ECCV)*, 2018.

12. C. Sanderson et al., ”Weapon detection using convolutional neural networks,” in *Proc. IEEE Int. Conf. Acoustics, Speech and Signal Processing (ICASSP)*, 2020.