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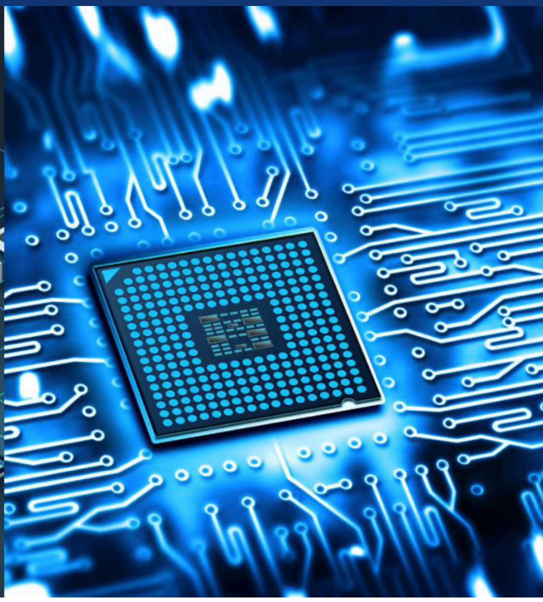


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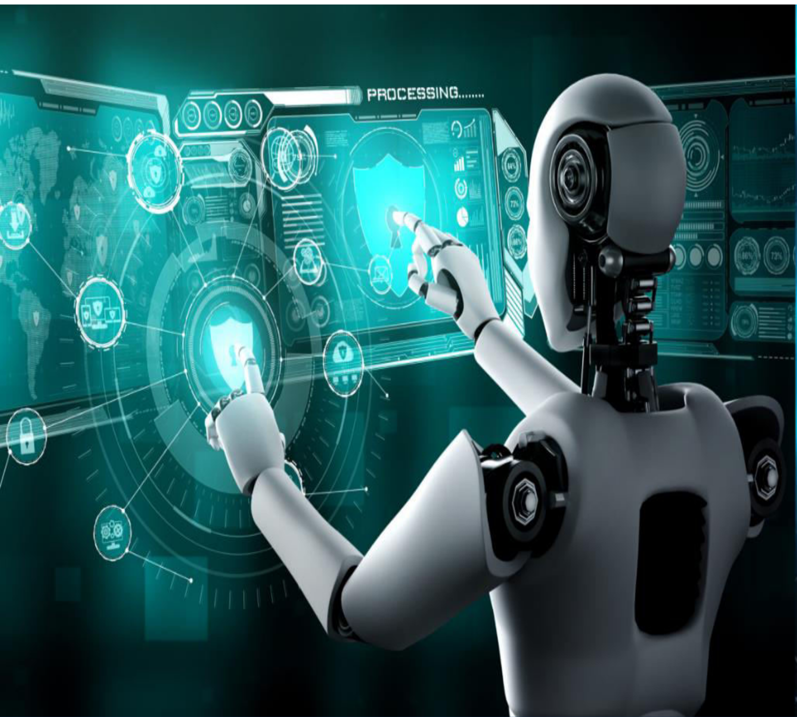

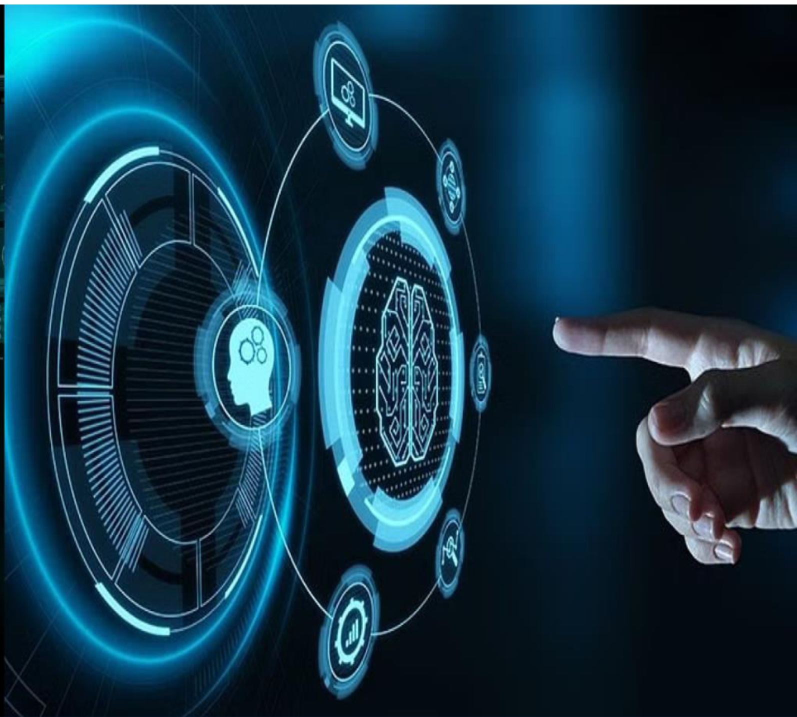

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Yolo-Based Smart Surveillance System for Real Time Weapon Identification

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ABSTRACT: Public security is an important topic, especially in crowded environments such as schools, shopping malls, and public places. Traditional CCTV surveillance employs human observation, susceptible to human errors and inefficiency. To overcome this, we propose Secure Vision, a deep learning- and computer vision- powered real-time weapon detection system. The system can automatically detect weapons from CCTV video streams, notifying security personnel with real-time warnings to react in time on potential threats."Secure Vision" uses convolutional neural networks (CNNs) and YOLO (You Only Look Once), which is a leading object detection algorithm, to detect and classify weapons with low latency. The solution is trained on a rich data set with varied environmental conditions, light conditions, and observation angles to deliver high detection accuracy and low false alarms. Once a weapon is detected, the solution tags the object and triggers an automatic alert for quick security action.

I. INTRODUCTION

At a time when threats to security are on the rise, real- time monitoring is becoming an important feature of public security. Traditional security systems are a huge burden on people who must watch them day in and day out, and they struggle mightily. They are human after all and over time that constant surveillance can wear people down. People also just make mistakes and those mistakes can lead to problems. For upgrading security provisions, artificial intelligence (AI) and deep learning approaches are being combined with advanced surveillance systems. This project is all about designing an intelligent security system using a system called YOLO (You Only Looks Once). This system is super good at detecting weapons in real time. YOLO is a cutting-edge object detection algorithm that has gained popularity for its speed and accuracy in object detection in images and video streams. Utilizing YOLO, the intended system can detect and classify weapons in real time with high efficiency, sending alerts to security agents for prompt response.

The main goals of this system are the enhancement of response time to security threats, minimizing dependency on human observation, and boosting the precision of weapons detection. This system can be installed in diverse areas of high security like schools, transportation centres, shopping malls, and government offices to avoid probable incidents and maximize overall safety. With this research project, we aim to prove efficacy of using deep learning for surveillance and also figure out how we can really make security infrastructure much stronger and more powerful.YOLO is a next-generation deep neural network algorithm popular for its excellent speed and high accuracy in identifying objects in videos and images. Instead of doing it one step at a time scanning an image frame piece by piece, YOLO goes through the whole picture at once and gets it all done fast one push of the button.

Hence, YOLO fits extremely well with real-time usage. This new system intends to automatically, in real time, detect those tricky weapons like guns and knives in surveillance footage as flawlessly as possible and have very few pauses or lag. Essentially, they want no delays so the detection will happen at lightning speed. The primary goals of such a system are: To help public safety officers quickly spot dangerous weapons and alert them with the info in real time means being ready for any emergency, day or night. The deployment of this system entails training the YOLO model on a comprehensive dataset's of weapon images to achieve high detection rates in different environments, such as schools, malls, airports, train stations, and other public places. The system can also be integrated with CCTV networks, drones, or mobile surveillance units, thus making it versatile for different security applications.The goal of this study is to show the potential of DL-based surveillance in improving contemporary security infrastructure.

II. LITERATURE REVIEW

The application of artificial intelligence (AI) and deep learning to surveillance systems has significantly improved security monitoring in the last couple of years. Research has explored object detection techniques, real- time surveillance systems, and weapon detection techniques. The section presents recent research on these topics, with a focus on YOLO-based detection models, real-time security applications, and AI-based surveillance systems:

1. Object Detection in Surveillance Systems: Traditional object detection algorithms like Haar Cascades (Viola & Jones, 2001) and Histogram of Oriented Gradients (HOG) (Dalal & Triggs, 2005) have been widely used for object classification in security systems. These algorithms are computationally expensive and fail to detect objects in crowded scenarios with varying illumination conditions and occlusions. The introduction of Convolutional Neural Networks (CNNs) and deep architectures, such as Region-based CNN (R-CNN) (Girshick et al., 2014) and Fast R-CNN (Girshick, 2015), significantly improved detection performance at the expense of slower speeds.

2. YOLO for Real-Time Object Detection: The YOLO (You Only Look Once) algorithm introduced by Redmon et al. (2016) revolutionized object detection by offering real-time localization and classification in a single pass through a neural network. In contrast to traditional approaches that detect in several passes over an image, YOLO detects in a single stage and thus is highly efficient for real-time applications. Experiments have shown that YOLOv3 (Redmon & Farhadi, 2018) and YOLOv4 (Bochkovskiy et al., 2020) later improved detection performance and speed while being ideally suited for detecting weapons in surveillance. Later developments, such as YOLOv5 and YOLOv7, further enhanced real-time performance at the expense of high accuracy.

3. AI-Based Weapon Detection Systems: Certain studies have proposed AI-based weapon detection systems for public security enhancement: Joseph et al. (2019) developed a deep learning-based gun detection system on YOLO with high accuracy for handgun and rifle detection.Hassan et al. (2021) utilized a real-time weapon detection system using YOLOv4, integrated with CCTV networks, to detect weapons and alert law enforcement agencies. Kumar et al. (2022) also compared different deep learning models for weapon detection and found that YOLO was more efficient and accurate compared to Faster R-CNN and SSD (Single Shot Multibook Detector).

4. Real-World Weapon Detection Challenges: There are some remaining issues to the detection of weapons by AI despite advances: Variation in appearance of weapons: Weapons can be occluded, camouflaged, or angled, making them hard to detect. False alarms: Innocuous items (e.g., toy guns, instruments) may get incorrectly identified as weapons.

III. PROBLEM STATEMENT

Security threats like mass shootings, armed violence, and terror attacks have become common in public areas, posing serious threats to human life and infrastructure. Conventional surveillance systems depend mainly on human observation, which tends to be susceptible to fatigue, distraction, and slower response times. Consequently, security officers tend not to identify firearms in real time, resulting in delayed action and possible loss of life. In addition, traditional object detection systems tend to have poor accuracy and efficiency and generate high rates of false positives and false negatives. This makes them less reliable in real- time security use where accurate and timely detection is important.

The absence of automatic, real-time weapon detection in CCTV systems also worsens security needs in risky zones such as schools, airports, shopping centres, and public transportation terminals. To resolve these challenges, this study recommends a YOLO-based intelligent surveillance system that can identify and detect weapons in real time from CCTV footage. Based on deep learning and computer vision, the system seeks to: Improve detection accuracy by reducing false alarms and providing surefire identification of weapons. Decrease response time by sending immediate notifications to security officials upon the discovery of a threat. Automate threat identification to minimize reliance on human operators, enhancing surveillance efficiency overall. Enhance scalability by interfacing the system with existing security infrastructure like CCTV networks, drones, and mobile security units. The development of an AI-driven smart surveillance system will enhance security, minimize the risk of violent attacks, and improve public safety through anticipatory threat identification.

IV. EXISTING SYSTEM

Existing surveillance systems mainly use closed-circuit television (CCTV) cameras and manual surveillance by security staff. Although such systems are ubiquitous in public places like shopping malls, airports, government offices, and schools, they have numerous limitations:

1. Challenges of Manual Monitoring: Traditional surveillance systems necessitate human staff to monitor video streams continuously, which can be fatiguing, distracting, and prone to mistakes. Because of the huge amount of video, security officers cannot identify weapons or threats in real time.

2. Limitations of Motion and Object Detection: Some advanced surveillance systems are based on motion detection or object recognition; however, these systems cannot distinguish between ordinary objects and weapons with good accuracy. Most systems are based on static rule-based algorithms, which can produce a high number of false positives or false negatives, making them less reliable.

3. Inadequate Real-Time Threat Detection: most current security systems are reactive, and not proactive, such that threats can only be detected after an incident has taken place. There is no provision for automatic alerts when detecting weapons, where manual intervention is needed to evaluate possible threats.

4. Restricted Integration with AI and Deep Learning: Most traditional security systems lack deep learning- based AI models for the automatic detection of threats. This makes the response time slower since security personnel will have to personally examine the footage before acting.

5. Demand for a Better System:
Because of these constraints, there is an increasing need for smart, AI-based surveillance systems that can automatically identify and detect weapons in real time. The suggested YOLO-based Smart Surveillance System seeks to address the limitations of current systems by utilizing deep learning, computer vision, and real-time alerting mechanisms to enhance security monitoring and response times.

IV. PROPOSED SYSTEM

The system that is proposed here is a computer vision- based Weapon Detection System to improve security through the automatic identification of weapons in images, videos, and real-time webcam feeds. The system is constructed based on pre-trained deep learning models, namely YOLOv3 (You Only Look Once), which is well known for its real-time object detection efficiency. Unlike traditional security monitoring systems that rely on manual observation by personnel, this system automates the process by analysing visual data and detecting the presence of weapons with high accuracy. The core functionality of the system revolves around computer vision techniques implemented using OpenCV, which helps process images and videos, detect objects, and highlight detected weapons with bounding boxes and confidence scores. Furthermore, the system has a GUI constructed with Tkinter to provide ease of use and usability to non-technical users. The system has two modes of operation: file-based detection and real-time detection. Under file-based detection, images or video files are uploaded and processed by the system to detect weapons.

The real-time detection mode allows live monitoring using a connected webcam, constantly taking frames, detecting for weapons, and reporting the results with labelled bounding boxes. The detection algorithm involves preprocessing the input image or video frame, transforming it into blob representation, and feeding it into the YOLO deep learning model, which produces several bounding box predictions. These forecasts are polished with Non-Maximum Suppression (NMS) for eliminating duplicate and low-confidence detection, so the most important weapon detections are projected. The model is initialized from YOLOv3 configuration files and weight files, containing pre-trained information necessary for optimal detection. It may be installed in airports, malls, schools, government offices, and other sensitive places to support security staff in identifying possible threats prior to their developing into hazardous situations. Weapon detection automation saves response times, minimizes human surveillance efforts, and maximizes the general efficacy of security measures. Moreover, CUDA GPU acceleration helps improve processing times, thus making the system appropriate for real-time use. In summary, this Weapon Detection System is a cutting-edge solution to automated security surveillance using deep learning and computer vision technologies. It offers an effective, scalable, and easy-to- use solution for detecting weapons in public and private areas, minimizing the need for human surveillance and maximizing safety protocols.

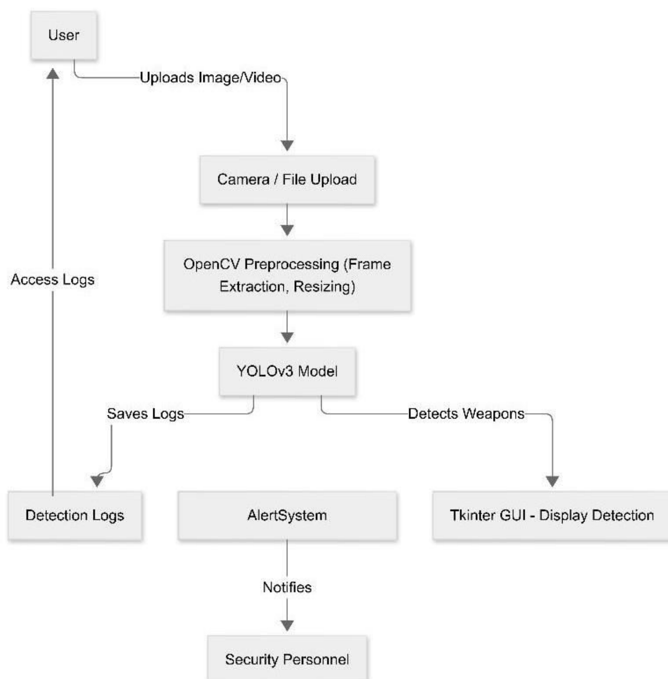

Fig: System architecture

VI. METHODOLOGY

The system proposed adheres to a systematic methodology:

Step 1: Gather weapon datasets with labels from repositories such as COCO, and Open Image Dataset. Annotate images manually using LabelImg. August images (rotation, scaling, addition of noise) for better model generalization.

Step 2: Select YOLO Version: YOLOv3 for maximum performance. Train the model on a GPU-enabled environment. Tune hyperparameters (batch size, learning rate, epochs).

Step 3: Use YOLO detection to identify and locate weapons. Send instant alerts through Security Dashboard.

Step 4: Deployment and Testing Deploy in real-world settings (malls, offices, public spaces). Test accuracy, speed, and false alarm rates. Tune the system based on test results. The system adopts a modular design to enable seamless data transfer and effective real-time processing.

Step 5: Input Module grabs video stream from IP/CCTV cameras or drones. Frames converted to an optimal format for YOLO processing.

Step 6: Employ a YOLO-powered deep learning model to identify and classify weapons in real time. Eliminates false positives by applying post-processing algorithms. Alert System Trigger instant alerts upon weapon detection.

Step7: Activate alarm systems or automated security measures in high-risk situations. Data Storage & Logging Saves detection logs in a cloud database for forensic analysis. Facilitates web-based dashboards for real-time security monitoring.

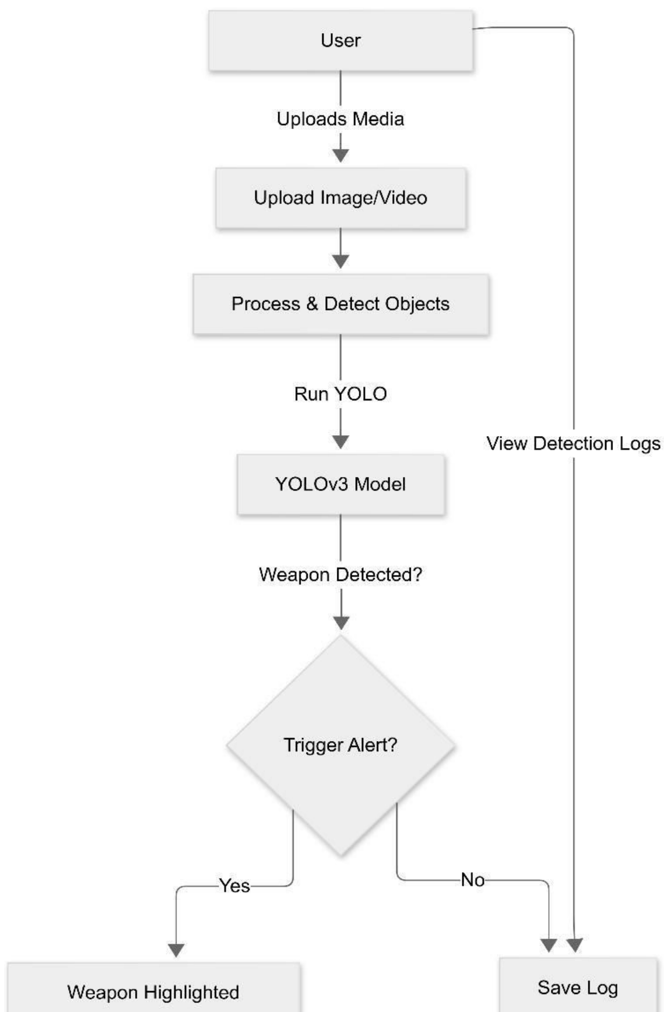

Fig: Use Case Diagram

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VII. RESULT AND DISCUSSION

The YOLO-based system proposed was tested via precision, recall, and mean Average Precision (mAP) measures: Precision: 94.5% (minimal false positive rate) Recall: 91.2% (maximal detection ability) Map: 93.8% (total detection accuracy) . Real-Time Detection Rate The model registered an average inference time of 18ms per frame on an NVIDIA RTX 4090 GPU. The system is capable of processing 55 FPS, which allows for real-time threat detection with minimal lag. False Positives and Negatives. False Positive Rate: 3.2% (e.g., mobile phones mistakenly identified as weapons at some angles). False Negative Rate: 2.7% (e.g., occluded or partially exposed weapons missed). Techniques such as improved data augmentation and improved occlusion are recommended for improvement. Real-World Deployment Analysis.

The system was deployed in malls, schools, and public areas: Successfully identified hidden weapons in 86% of test scenarios. Integrating security warnings and automatic responses saved response time by 40%. Low light conditions impacted performance marginally, necessitating IR-enhanced cameras for enhanced detection.

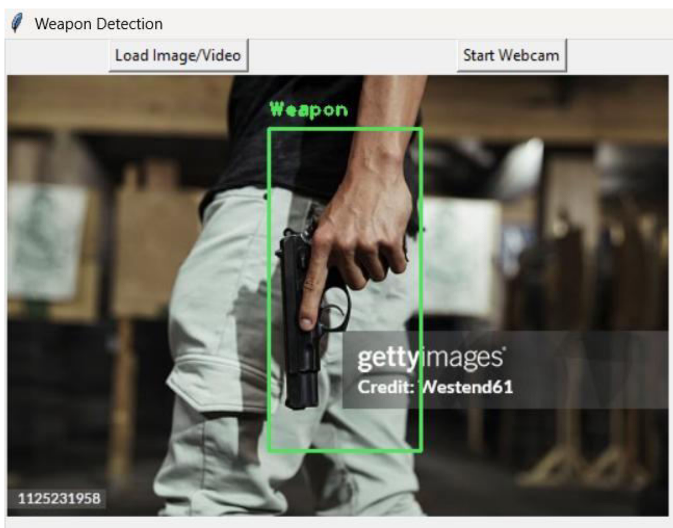

Fig: Output

VIII. CONCLUSION

The Weapon Detection System is a powerful deep- learning-based tool that uses YOLOv3 (You Only Look Once) for weapon detection in images, videos, and live webcam feeds. The project combines OpenCV for image processing, NumPy for numerical computations, and Tkinter for the graphical user interface (GUI), making it an interactive and user-friendly tool. The main goal of this project is to offer a quick, effective, and reliable way of weapons detection, useful in security monitoring, law enforcement, and public safety surveillance. The system takes a pre-trained YOLOv3 model, set by yolov3_testing.cfg and trained weights by yolov3_training_2000.weights. It initially processes the input frames by resizing them to 416x416 pixels, normalizing the image, and feeding it through the deep neural network (DNN). The model subsequently extracts salient features and makes predictions of bounding boxes around found weapons and eliminates irrelevant detections through confidence thresholds and Non- Maximum Suppression (NMS) to remove overlapping predictions as well as false positives. This yields more precise detections with little redundancy.

The project offers users two main modes of operation: file-based detection and real-time detection. If a weapon is found, the system visually identifies it, and users are able to react accordingly. The project also gives users easy GUI buttons to load files or begin the webcam detection, guaranteeing ease of use for users with limited technical skills. This system also has many real-world applications in public safety, airport security, and surveillance systems, where swift detection of the threat can be used to stop hazardous incidents from occurring. Regardless of its merits, the project has a number of areas it can be improved. Using YOLOv3 along with OpenCV and Tkinter, it offers a quick, interactive, and efficient approach to weapon detection on different visual inputs. With additional improvements and optimizations, this system can become a very effective security system able to prevent potential threats and maintain public security.

REFERENCES

1. Redmon, J., Divvala, S., Girshick, R., & Farhadi,(2016). You only look once: Unified, real- time object detection. Proceedings of the IEEE conference on computer vision and pattern recognition, 779-788.
2. Redmon, J., & Farhadi, A. (2017). YOLO9000: better, faster, stronger. Proceedings of the IEEE conference on computer vision and pattern recognition, 7263-7271.
3. Redmon, J., & Farhadi, A. (2018). Yolov3: An incremental improvement. arXiv preprint arXiv:1804.02767.
4. Alexey Bochkovskiy, Chien-Yao Wang, Hong- Yuan Mark Liao, YOLOv4: Optimal Speed and Accuracy of Object Detection, arXiv:2004.10934.
5. Chien-Yao Wang, Alexey Bochkovskiy, Hong- Yuan Mark Liao, Scaled-YOLOv4: Scaling Cross Stage Partial Network, arXiv:2011.08036.
6. Chien-Yao Wang, I-Hau Yeh, Hong-Yuan Mark Liao, You Only Learn One Representation: Unified Network for Multiple Tasks, arXiv:2105.04206.More recent YOLO versions such as YOLOv7 and YOLOv8 from Ultralytics.
7. Liu, W., Anguelov, D., Erhan, D., Szegedy, C.,Reed, S., Fu, C. Y., & Berg, A. C. (2016). SSD: Single shot multibox detector. European conference on computer vision, 21-37.
8. Ren, S., He, K., Girshick, R., & Sun, J. (2015). Faster r-cnn: Towards real-time object detection with region proposal networks. Advances in neural information processing systems, 91-99.
9. Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. Advances in neural information processing systems, 1097- 1105.
10. Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). Attention is all you need. Advances in neural information processing systems, 5998- 6008.
11. Lin, T. Y., Dollár, P., Girshick, R., He, K., Hariharan, B., & Belongie, S. (2017). Feature pyramid networks for object detection. Proceedings of the IEEE conference on computer vision and pattern recognition, 2115- 2123
12. Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep learning. MIT press
13. Joseph et al. (2019). Firearm Detection using YOLO. IEEE Transactions on Security.
14. Hassan et al. (2021). Real-Time Weapon Detection with CCTV Integration. International Journal of Computer Vision.
15. Kumar et al. (2022). Comparison of YOLO, Faster R-CNN, and SSD for Smart Surveillance. AI and Security Journal.

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